ESSAYS ON POVERTY REDUCTION IN LATIN AMERICA

BY

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ABSTRACT

In recent years, reducing poverty has been a core objective of social policy in Latin America. In 2008, the incidence of poverty reached almost a third of the population, of which 13 percent are classified as extremely poor. Most Latin American countries have invested vast resources in poverty reduction programs, particularly Conditional Cash Transfer schemes (CCTs), which have become a critical element in social policy.

The effectiveness of CCTs has been a hotly debated topic. Most social programs in Latin America lack data for comprehensive evaluations to be carried out, but CCTs are an important exception. Many programs have been designed to have measurable impacts on various outcomes, generating a variety of empirical evidence that has been critical for designing and implementing new CCTs as well as fine-tuning existing programs. Evaluations cover a range of issues from access to education and health services, consumption patterns, to the impact on poverty, inequality, and labor market participation. Structural models of household behavior as well as empirical modeling of program implementation have been used to study the effectiveness of the conditionality and the size of the cash transfer. Nonetheless, the design of CCTs can be improved by better understanding households' behavior in different environments as well as by constantly revising program rules such as transfer's schemes and targeting instruments. CCTs have proved to be an effective form of social assistance, but are not a panacea to eradicate poverty.

A careful examination of which factors generate disparities in living standards is crucial to design poverty reduction interventions. A common feature in many Latin America countries is the presence of geographic disparities in living standards that persist over time, in spite of growth at the national level. The role of infrastructure and geography vis-à-vis human capital and other determinants of household consumption growth have the potential to explain how aggregate economic growth translates into changes in household welfare. Moreover, researchers and policymakers alike are aware that the appropriateness of poverty reduction programs includes an in-depth analysis of geographical characteristics to aid the design of effective policy interventions to reduce poverty. For example, a better understanding of the geographical distribution of poverty can help fine-tune existing CCTs. The essays presented contribute to the literature on analytical work on poverty reduction programs, the effects of these programs on human capital accumulation and propagation of poverty, and the geographic determinants of household consumption.

The first two papers analyze Mexico's Conditional Cash Transfer Oportunidades. Mexico's CCT is one of the oldest in Latin America and currently reaches 5 million households, one fourth of the country's population. In terms of budget, the program costs about 0.5 percent of the country's gross domestic product (GPD) and the transfers represent around a fifth of the mean household consumption. As in many other CCT, *Oportunidades* has two main objectives: reduce poverty in the short run and increase the human capital of children, which weakens the transmission of poverty across generations. To reach the second objective, transfers are conditional on household investments in children's education, health, and nutrition. The first two of papers in this dissertation proposes analytical tools to fine tune the current design of *Oportunidades* along two dimensions. First, it analyzes the program current targeting system and proposes an alternative

methodology to select beneficiaries. This is important for program effectiveness (measured as a reduction in targeting errors) and fairness, since the program's objective is to reach the poorest households that under invest in the human capital of their children. Second, the paper assesses how a critical aspect of *Oportunidades*, school enrollment, changes in response to a new scheme of transfers and the corresponding costs in terms of the program's budget.

The first paper proposes a multidimensional targeting instrument that identifies CCT beneficiaries more efficiently by selecting beneficiaries with deprivations on the dimensions that are aligned with CCTs objectives. Targeting mechanisms used by CCTs have been generally successful in identifying the income poor, but have fared less well in identifying households that under-invest in children's human capital. CCTs have applied targeting mechanisms based on proxy means test, generally variants of principal component analysis, probabilistic models or ordinary least square regression that identify monetary or well-being composite measures. Nonetheless, CCTs have traditionally identified their beneficiaries comparing the welfare metrics against a single threshold or cut-off point (or "unidimensionally"). The paper proposes a novel multidimensional approach to identify program's beneficiaries that accounts for the multiple objectives of the CCTs and the multiple deprivations of the household. The proposed targeting mechanism is applied to the Mexican urban program *Oportunidades* and significantly improves the selection of households with children who are most deprived in the dimensions often relevant to CCTs (e.g. poor households with children that are not attending school). A robusteness exercise is carried out using an ex-ante evaluation technique that reinforces the contribution of the proposed targeting mechanism.

The second paper uses an occupational choice model to ex-ante evaluate the impact of different transfers' schemes on school enrollment and child labor. This paper assesses the occupational choice model of Bourguignon, Ferreira and Leite (2003) as a well suited technique to simulate the impact of policy changes in traditional CCT programs. This is important because one of the main setbacks of ex-ante evaluations is that the choice of the model can lead to 'targeted modeling' indicating that the results might be driven by the features of the model rather than the policy itself. Furthermore, we relax the model's identifying assumption and simulate alternative transfer's schemes with the objective of increasing school attendance. The findings indicate that the model predicts well school attendance and is a valuable technique to analyze ex-ante the impact of policy changes in school enrollment and its subsequent effects on poverty and inequality indicators. One of the counterfactual simulations indicate that eliminating or reducing school subsidies for primary education and increasing transfer for older students is a cost-effective way to raise overall school enrollment. Another result indicates that increasing school attendance of 16-year-olds to 80 percent or more requires a substantial increase in the transfers.

Another key stylized fact in the poverty literature is the existence of poverty traps. From the beginning of the development theory, poverty traps have called the attention of researchers and policymakers alike. As defined by Azariadis and Stachurski (2005) "A poverty trap is any reinforcing mechanism that causes poverty to persist." At the macro level, the concept of a poverty trap has been used to explain differences observed in per capita income between countries and in the case studied in this paper within regions of a country.

The third paper sheds light on the spatial distribution of poverty, and the intra-regional dynamics of income distribution within a country (Ecuador). The paper assesses the importance of geographical, physical, and human capital variables in explaining differences in consumption growth in Ecuador— a country characterized by significant geographical and cultural heterogeneity. In particular, the paper uses novel *pseudo-panel data* techniques to analyze the link between geographic factors and household welfare. The evidence indicates that geographical variables are important determinants of the household consumption growth after accounting for household characteristics such as education and labor market experience. Furthermore, the results indicate that individuals with similar characteristics experience increments in growth levels differently, depending on where they reside. Altogether, the results indicate that in other to reduce poverty, efficient and equitable government policies should take into account the role of geography and geographical diversity, including the regional distribution and provision of public goods.

To my children Raphael and Laura, my parents,
and my husband Roberto.

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1. Introduction

Conditional cash transfer (CCT) programs have in general two main objectives: to alleviate poverty by raising the purchasing power of the household and to develop the human capital of children to break the intergenerational transmission of poverty. In order to reach these objectives, CCTs provide cash to poor households on the condition that they make pre-specified commitments such as investing in their children's human capital. During the 1990s many developing economies adopted CCTs, which are now among the largest social assistance programs in Latin America, covering millions of people; in Mexico and Brazil, CCT benefits a fifth of the population, and in Ecuador forty percent (Fiszbein and Schady 2009).[1] At the present time almost every country in the region has a CCT program or is in process of implementing one.

Conditionality and targeting are two essential features of CCTs. In the majority of these programs, the conditionalities take the form of co-responsibilities, that is, a form of social contract between the state, civil society, and beneficiaries. Conditionalities ensure investments in children's human capital and help justify income transfers to those who object to targeted transfers as "pure handouts", because program beneficiaries take a number of concrete steps in favor of children's well-being. Targeting is the other major feature of CCTs. A targeting mechanism aims at answering a simple question: who should benefit from a given development initiative? Targeting methods are essential components of social safety net programs, and are especially attractive for poverty reduction programs, such as CCTs (Grosh et al 2008). By allocating resources to the fraction of the population that needs it the most, a benevolent policy maker can increase benefits for a given budget or can achieve a bigger impact with the lowest cost. In parallel to the efficiency argument, targeting is also supported as a redistributive mechanism; equity considerations aims at targeting certain groups that are more likely to be

[1] Rawling and Rubio 2005 show the specific differences in CCTs programs for six Latin American countries.

vulnerable (according to certain ascribed characteristics such as age, gender, and membership of a marginalized group). Furthermore, targeting mechanisms are also necessary to compensate for geographical welfare disparities, such as isolated regions or rural localities (Fiszbein and Schady 2009).

As a result of the emphasis on the poverty criteria for targeting beneficiaries and the explicit use of targeting mechanisms to determine eligibility, CCT programs have shown significant redistributive results. The transfers are pro-poor and the coverage rate in the lowest deciles of the income distribution is high (around 45 percent of the CCT transfers are given to the poorest 20 percent of the population). After analyzing the redistributive power of 56 transfers programs in eight Latin America countries, Lindert *et al* 2006 show that CCTs are the class of programs with better targeting performance among all kinds of social spending in the region.

Despite the undeniable success of the CCT programs, current targeting mechanisms have been criticized for excluding poor households of the program. This is especially true when the CCT covers a large number of households or in the more heterogeneous urban areas. Furthermore, there is also empirical evidence suggesting that exists room for improving the performance of current targeting models (Coady *et al* 2004a, Coady and Parker, 2009).

In view of this, the present paper proposes a new targeting methodology using a multidimensional approach that satisfies a set of axioms and can simultaneously encompass the two criteria that define the target objective of CCTs: poverty and under-investment in human capital. We propose a set of dimensions, indicators, and weights in tune with the essential objectives of CCT programs and use traditional and ex-ante microsimulation techniques to evaluate the performance of the proposed targeting model. We find that the multidimensional model identifies the monetary poor more precisely than the current *Oportunidades* targeting model, and selects households with characteristics that are more in line with the program objectives (for example, the multidimensional model is better at identifying households that do not send children to school). Another important result regards the expected impact of transfers in the occupational choice of children. The results of an ex-ante evaluation show that program's transfers have a greater impact on school attendance of potential beneficiaries selected by the multidimensional model relative to that of alternative targeting models.

The remainder of the paper is structured as follows. Section 2 describes current CCTs targeting models and their limitations, while Section 3 focuses on the Oportunidades targeting. Section 4 describes the methodology for identifying beneficiaries of CCT programs based on a multidimensional approach to poverty measurement (Alkire and Foster 2008); section 5 outlines and applies the methodology to the urban case of *Oportunidades*; section 6 evaluate the performance of new targeting methodology, and section 7 presents the concluding remarks.

2. A review of CCT's targeting strategies

In order to reach the poorest households, most CCT programs have used several targeting mechanisms. The most commonly used targeting sequencing has been generally geographic targeting followed by household proxy-means test. Based on the information of a poverty map, the poorest localities are chosen to participate in the program—geographic targeting. After selecting localities, a census takes place to capture information about households' main socioeconomic characteristics. Using data from this census, households are classified as "eligible" or "non-eligible" for the program through a proxy-means test—a formal algorithm used to proxy household welfare based on households' information and individual characteristics. Other forms of means-tests are the unverified means test used in Brazil and the verified means test, the gold standard of the means-test, used in the United States. The targeting mechanism that identifies households as potential beneficiaries is known as household or individual targeting. In addition, some programs use community-based targeting or community vetting of eligibility lists to increase transparency. Fiszbein and Schady 2009 have shown that about two thirds of countries that have CCTs programs use geographic targeting; about two thirds use household targeting, mostly via proxy-means test; and many countries use a combination of geographical and proxy-means. Finally, a self-targeting takes place, since once households are notified of their eligibility they must decide whether or not to participate in the program.[2] Some programs implement self-targeting as the first targeting mechanism, requiring households to pre-register for the program. The importance of each targeting mechanism may be different according to stages and size of the program. The role of geographic targeting tends to be reduced and that of the proxy-means test to increase as the program reaches national coverage or expands to less deprived localities (Coady 2006; Grosh *et al* 2008; Coady and Parker 2009).

The statistical methods used in proxy-means tests and their sophistication vary substantially across CCT programs. A proxy-means test generates a score (a probability or an index) for each potential beneficiary household. To calculate this score, indicators—which must be easily observable characteristics—are selected and their respective weights are obtained from statistical analysis using information from a detailed national household survey. The diversity of the methodologies within Latin America samples the alternatives being used. Costa Rica and Jamaica estimate a consumption model based on simple OLS regression; Colombia and Ecuador construct a well-being index based on principal components analysis; Uruguay opts for a poverty model based on probit analysis; and Mexico defines a poverty score based on discriminant analysis.[3] Eligibility is determined by checking the score—linear combination of selected indicators and its corresponding weights—against a particular cutoff point or poverty line. In other words, the proxy means test generates a poverty measurement used to define household eligibility. Proxy- means tests are a promising cost-effective alternative for targeting cash transfers in developing countries, especially when high degrees of informality in the labor market exists, which hinders the collection and verification of detailed information on household income or consumption levels (Coady *et al* 2004b; Castaneda and Lindert 2005). Since it was first implemented in Chile in the 1980s, proxy-means tests have been monitored and its implementation and use refined over the years (Larrañaga 2003; Coady *et al* 2003).

Researchers and policymakers are aware of the CCTs' targeting errors. Important recommendations have been made to improve the performance of current proxy-means,

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[2] For an exhaustive review and evaluation of targeting mechanisms see Coady et al 2004b.

[3] Significant variations also exist in how the implementation is done —whether households are visited; whether some variables are verified as part of the application process for all or for a sample of applicants; whether the staff members who help complete applications are permanent or contract workers and to which agency they report; and other such differences

including: (a) using the latest information to obtain up to date weights; (b) incorporating socio-economic variables that are more stable over time and are less susceptible to manipulation by the informants—for instance, household attributes at the geographical level; (c) estimating current models differentiating residence areas; (d) changing the cutoffs to acceptable levels of leakage (proportion of household that are program beneficiaries and are not poor) or under-coverage (proportion of poor household that are not beneficiaries of the program), (e) using alternative estimation methods (for example, logistic regression instead of discriminant) or modifying the dependent variable of current specifications (for example, using income directly rather than poverty status), (f) improving the quality of information obtained from the potential beneficiaries through additional controls in the whole process of the data collection (DNP 2003; Coady and Parker 2004; Rubalcava 2004; Catañeda and Lindert 2005, among others).

While the above recommendations are useful, they do not address a major shortcoming of current targeting methodologies: poverty is considered essentially a monetary phenomenon. Academics and practitioners are progressively acknowledging the multidimensional nature of poverty. The argument is that income deprivation does not necessarily reflect well deprivations in other important dimensions such as health and education. In fact, the notion that a higher income would allow a household to deal with all other deprivations is based on the assumption that there are competitive markets for goods and services related to the health care of children, nutrition, and education. However, education as well as other public goods are provided in imperfect markets, and therefore, higher income does not always permit a household to face its deprivations (Tsui 2002; Bourguignon and Chakravarty 2003).

Many may argue that the targeting methods currently used by CCT programs take into account the multidimensionality of poverty, since a variety of household characteristics are included in the proxy-means test used to compute the score. However, this is not a truly multidimensional approach, but a rather unidimensional one: it does not capture each dimension-specific deprivation. If one agrees that poverty is multidimensional, but uses an income approach to reach the poor, there is a significant risk of mistargeting. Additionally, the literature has pointed out that such models leave open the possibility of two or more equally valid models generating different conclusions about the level of household poverty (Duclos *et al* 2006) and that they usually produce poverty measures that violate some important desirable axioms that a multidimensional index must respect (Bibi 2005).

The CCT targeting models used so far have been explicit to reach the income criterion, but less focused on the under-investment in human capital. In other words, the targeting has not been aligned with CCTs' objectives and its target population.[4] After the selection of a geographical area, while the monetary poverty of household has been directly estimated with a proxy-means test, the human capital has been identified indirectly through demographic characteristics (households that have children in the "right" age group and pregnant and lactating women). Consequently, the relative success of CCTs in reaching poor households has been focused primarily on the monetary dimension of poverty and less on other relevant dimensions.[5]

To take in consideration the two criteria for eligibility of the target population (poverty and investment in human capital), a few countries have used innovative targeting strategies to better identify its target population. For example, the Chile Solidario CCT program applies a "dual targeting" mechanism to identify beneficiaries. First, poor households are identified with a traditional proxy-means test and then a social worker in conjunction with the household identifies how the household under-invests in human capital in order to agree on minimum conditions that must be reversed (Fiszbein and Schady 2009). This is an alternative that can be very effective, but that involves high costs for the program as it requires intensive interaction between the household and the social worker, not only for diagnosis but also for monitoring.

3. The targeting of *Progresa-Oportunidaes* program

[4] The target population of CCTs are poor households that under-invest in the human capital of their children (Fiszbein and Schady 2009).
[5] For example, although the Panama's CCT has reached a number of households similar to the size of the target population, two important groups of extreme poor are not beneficiaries of the *Red de Oportunidades*: 67 percent of children aged 6 to 14 years old that does not attend school, and 48 percent of the children aged 0 to 4 years old that has chronic malnutrition. These calculations are available upon request.

One of the oldest CCT programs is the Mexican program *Oportunidades*, formerly called PROGRESA. This program was implemented in 1997 and since then it has increasingly been expanding its household coverage. In 2009, the program reached all the country's municipalities and virtually all of its localities, covering around a fifth of all households. The evidence has shown that this is one of the CCT programs with bigger impacts on the population's well-being (Rawlings and Rubio 2005; Handa and Davis 2006) and with better performance in terms of the distributive impact (Lindert *et al* 2006; Levy 2006). There is also evidence that the income transfers under PROGRESA-*Oportunidades* program are successful in improving health indicators, increasing school attendance, and reducing current poverty as well as inequality indicators (Levy 2006; Fiszbein and Schady 2009).

The program selects its beneficiaries through a two-stage targeting strategy that combines geographic targeting and proxy-means testing. Since its beginning, the first stage consists of the identification of poorer localities based on a "marginality index" constructed with information from the population census data and the application of principal components analysis. For the final geographical selection, the program takes into consideration the availability of a minimum supply of health clinics and schools, so that households can comply with co-responsibilities. The second stage of the process involves the identification of eligible households, within the localities selected in the first stage, by applying a proxy-means test. To this end, the program collects socioeconomic information of the all households living in intervention localities through the implementation of the ENCASEH in rural areas and ENCASURB in urban areas. [6] In urban localities with a low "marginality index" a preliminary self-selection of families into the program takes place: first, the families voluntarily ask to be incorporated into the program, at that point household information is collected (first at the local office and then at the household). During the first phase of the rural expansion program, the targeting process also included an additional stage, based on a validation through community assemblies of eligible household lists, which aimed at correcting leakages or under-coverages of the first two stages.

[6] ENCASEH is the Spanish acronym of National Survey of Household Socioeconomic Characteristics and ENCASURB of National Survey of Urban Household Socioeconomic Characteristics.

Between 1997 and 2001 the proxy means test equation was estimated separately for 41 groups of rural localities using information from the ENCASEH and discriminant analysis technique (Regional Scoring System). In 2002 the targeting mechanism was changed as the program expanded to urban areas. This led to the development and estimation of a new scores model: Unique Scoring System (SUP is the Spanish acronym for "Sistema Unico de Puntajes"), estimated using economic poverty as dependent variable, discriminant analysis, and a single source of national information (ENIGH[7] 2000). The estimation takes into account the heterogeneity between the rural and urban areas as well as other regional disparities in the specification of the single equation. A household is eligible according the SUPs if its score exceeds a given cut-off point.[8] The SUP is the proxy means model currently being used to determine eligibility of households for purposes of entry and continuity in the program.

The Mexican program is perceived to be well targeted, has been evaluated extensively, and has been used as a benchmark by other CCTs. Evaluations of the targeting strategy were carried out at different stages of the program, leading to adjustments and refinements of the mechanism as the program expanded. Behrman *et al* 1999 analyze the rural targeting of PROGRESA and show that the method used to target beneficiaries at that point was the most cost-effective to reduce poverty (severity and depth) in comparison with consumption-based targeting or geographical targeting. The authors point out that exclusion errors were occurring as the targeting mechanism failed to identify households with a small number of members or households without young children. Evaluations of the expansion to urban areas, which includes self-selection as households request to be beneficiaries of the program, indicate that the targeting mechanism is sound, although its predictive power is reduced in relatively richer communities and with households that are close to the poverty line. A quantitative evaluation by Coady and Parker 2004 find under-coverage of about 24 percent and leakage of about 22 percent. The authors point out that the leakage does not seem to be very critical, as around 15 percent of these households were close to the poverty line. A qualitative evaluation carried out by Escobar and Gonzales de

[7] The ENIGH is the Spanish acronym of National Survey of Household Income and Expenditure, the nationally representative household survey.

[8] The value currently used by the program is 0.69. For more details on the targeting mechanism of PROGRESA/Oportunidades, see Orozco and Hubert 2005, Regalia and Robles 2006, and Coady and Parker 2009.

la Rocha 2003 shows that the targeting mechanism was positively perceived by households as it bypasses political affiliations and local leaders.

Comparative evaluations shed light on the performance of different targeting methods. Skoufias et al 2001 analyze the contribution of the different targeting methods used by PROGRESA in rural areas and compare the program's method to alternative selection methods and universal targeting. The results indicate that PROGRESA's targeting method is more effective in identifying the extremely poor localities or households but not as good at discriminating among localities or households in the middle of the income scale. Furthermore, the authors point out that the results of the geographical targeting "raises some serious questions about the costs and benefits associated with the practice of household targeting within poor localities". This is further analyzed by Coady 2006 who extends the previous work and evaluates the relative incremental contribution of different targeting mechanisms including demographic targeting and self-selection in the first 130 rural localities beneficiaries of the program. The author concludes that the contribution of the individual targeting (proxy-means) could increase as the program expands to less deprived localities. Finally, Coady and Parker 2009 evaluate the relative contributions of two different targeting methods in urban areas: an initial self-selection process by households who acquire knowledge of the program and a proxy means test. They consider performance in terms of the effectiveness of the program at channeling a high proportion of benefits to lower welfare households. Their findings highlight the importance of proxy means targeting in the context of universal knowledge, and call for further improvements in this mechanism to reduce targeting errors.

3.1 There is room for improving targeting in the urban Oportunidades CCT

Despite the huge expansion of *Oportunidades* and the success of its targeting mechanism in the first years, the program's coverage of poor households has become a major challenge in recent years. The most recent nationally representative household survey (ENIGH 2008) shows that the program benefited 714 thousand urban households and 3 million 521 thousand rural households, equivalent to around 30 percent and 120 percent of the urban and rural poor, respectively.[9] The latter implies that *Oportunidades* reaches only 14 percent of urban poor households and 59 percent of rural poor households. The empirical evidence suggests that the relationship between poverty and the variables of the current household targeting model (SUP) has eroded as the poverty profile has changed. Table 1.1 shows that, on average, the poor have improved in the variables currently considered by the program's targeting model, a result that calls for a revision of the current targeting mechanism. Table 1.1 also displays the average correlation between income poverty and each of the independent variables of the SUP model (discriminant equation). The correlation is reduced by 26-27 percent from 2000 to 2006, affecting the model's predictive power to distinguish between poor and non-poor households. As highlighted by Coady and Parker 2009 "improvements in the proxy-means algorithm to increase its correlation with welfare can help to further decrease under-coverage and leakage". Finally, the ENIGH 2008 shows targeting errors regarding dimensions that go beyond the monetary dimension: 44 percent of Mexican extremely poor children aged 9 to 18 years old that do not attend school are not beneficiaries of the program, that is, children living in poor households that are not investing in the human capital of them.[10]

4. A multidimensional approach to targeting

4.1 A brief review of the multidimensional poverty literature

Although a wide branch of the empirical work on poverty still uses a one-dimension measure to judge a person's well-being, usually per capita income or consumption, there is a widespread consensus that income itself is an incomplete measure to human deprivation. As highlighted before, the rationale is that a person with a higher income level may be able to improve some of his monetary and non-monetary attributes, but markets for some non-monetary attributes may not exist or could be highly imperfect (Tsui, 2000; Duclos et.al, 2001; Bourguignon and

[9] In Mexico there are three official poverty lines. Throughout the text the poverty definition used is the capability poverty (pobreza de capacidades) since it is the poverty line used by the *Oportunidades* program which is defined as follows: the inability to obtain a basic food basket and meet the necessary health and education expenses, even if the household were to use all its available income solely for these purposes (CONEVAL2007).
[10] Calculations are available upon request.

Chakravarty, 2003; Atkinson, 2003). This implies that individual's well-being has dimensions that cannot be purchased and therefore if income is the sole indicator of well-being, it is inappropriate and should be supplemented by other attributes or variables.

The idea that there are many facets to poverty and deprivation has been well studied in the literature. The work of Sen 1992 highlights the need to go beyond income as he proposes that poverty should be seen as a capability deprivation, where living is seen as a set of interrelated functionings (or outcomes) consisting of beings and doings. Another example is the *Theory of Justice* of Rawls (1971) that has been also very influential for this line of thinking. Rawls proposed that ensuring the well-being of a person required for some basic needs to be met. These needs are regarded as the means that are necessary for people to take part in the life of their society and include economic means as well as institutional rights and freedoms (Freeman, 2007).

Despite the important amount of literature on multidimensional poverty and deprivation, as far as we know, no single multidimensional welfare index has received unanimous approval. There are ethical and empirical considerations that are usually polemic in constructing a multidimensional welfare indicator. Decisions have to be made on (i) the definition of the welfare dimensions to consider; (ii) the weight of each dimension; (iii) deprivation cutoffs for each dimension; (iv) definition of the second cut-off or the multidimensional poverty line, among others. The debate regarding the relevant dimensions and their relative importance has lead to an increasing supply of multidimensional well-being indicators, sometimes yielding different results (Battiston et.al., 2009 Decancq and Lugo, 2008).

Among the multidimensional poverty indicators, some have received more attention than others. Tsui (2002) clarifies the axiomatic basis for the design of multidimensional poverty measures and generalizes the class of subgroup consistent poverty indices introduced by Foster and Shorrocks (1991) to a multidimensional framework. Bourguignon and Chakravarty (2003) examine various aggregation rules using different postulates for a measure of poverty, making a distinction between additive and non-additive poverty measures. Atkinson (2003) adopts a social welfare function approach, based on Bourguignon and Chakravarty methodology, and brings out the role played by the cardinalization assumptions (the degree of concavity of the social welfare function) and the weighting of different attributes. He distinguishes two different forms of aggregation. The first one combines different elements of deprivation at the individual level, which are then summed over individuals first to form an aggregate index for the country. The second one sums across individuals first, to form a total indicator for all individuals in one dimension, and then combines the total indicators for different attributes.

Several empirical applications of the multidimensional welfare measures following the above described methodologies exist. Bourguignon and Chakravarty (2003) apply their measures to evaluate the evolution of poverty in rural Brazil in the 1980s. Paes de Barros et.al. (2006) introduce a scalar indicator to estimate the degree of multidimensional poverty of families using Brazilian household surveys. Krishnakumar and Ballon (2008) operationalize the capability approach using the latent variable methodology. They specify a structural equation model for Bolivia to account for the unobservable and multidimensional aspects that characterize human development. Battiston et.al. (2009) calculate multidimensional poverty measures for six Latin American countries (Argentina, Brazil, Chile, El Salvador, Mexico, and Uruguay). Their estimates are based on the extensions developed by Alkire and Foster (2007) and Bourguignon and Chakravarty (2003); their study incorporates the weighting of different dimensions derived from a participatory study on the voices of the poor performed in Mexico. The results indicate large differences between countries and also within countries between urban and rural areas and conclude that increasing the access to proper sanitation and improving education should be policy priorities as they are the highest contributors to multidimensional poverty.

Finally, Alkire and Foster (2008) have proposed a new methodology for multidimensional poverty measurement consisting of an identification method that extends the traditional union and intersection approaches, and the Foster, Greer and Thorbecke (FGT) class of poverty measures. We follow Alkire and Foster in what follows, a proposal for multidimensional targeting.

4.2 Multidimensional targeting: A proposal

This sub-section describes the proposed household targeting methodology which draws from the identification step of the family of multidimensional poverty measures developed by Alkire and Foster (2008). Such family of measures satisfies a set of properties considered desirable in poverty measurement.[11] The identification implies –first– defining a cutoff point for each considered dimension, and –second– defining an *across-dimensions* cutoff, as the number of dimensions in which the household should be deprived so as to belong to the poor group. The second cut-off is the novelty of the approach. So far, the existing approaches to multidimensional poverty measurement are usually confined to using one of the two extreme approaches to the identification of the poor: "union" or "intersection". The first requires households to be deprived in at least one dimension, while the second requires them to be deprived in all considered dimensions. While Alkire and Foster's approach allows for these two typical extreme criterions, it also allows for intermediate –and likely more useful– cases. In what follows we formally present the proposed targeting methodology.

Let $y = [y_{ij}]$ be the matrix of achievements, where each element y_{ij} is the achievement of household $i = 1, \ldots, n$ in dimension $j= 1, \ldots, d$. The achievements can be either continuous such as income or consumption or discrete such as years of education. Let z_j be the deprivation line or cutoff point for dimension j. Then one can define the deprivation matrix $g^0 = [g^0_{ij}]$. Each element g^0_{ij} is such that

$$g^0_{ij} = \begin{cases} 1 \text{ if } y_{ij} < z_j \\ 0 \text{ if } y_{ij} \geq z_j \end{cases}$$

That is, the elements of the deprivation matrix take the value of 1 if the household is deprived in dimension j and the value of zero if the household is not deprived in dimension j.

Suppose also that each dimension has a weight attached, so that there is a row vector $w = [w_j]$, where w_j is the weight associated with dimension j. The weights are such that they add up to the total number of dimensions d. Based on matrix g^0 weighted by w, one can obtain a column

[11] Among the latest reviews of these assumptions is the study conducted by Kakwani and Silber 2008.

vector $c = [c_i]$ where each element c_i indicates the sum of weighted deprivations for each household i

$$c_i = \Sigma g^0_{ij} * w_j$$

At this point the second cut-off value needs to be defined; this will indicate the number of weighted deprivations in which the household needs to be deprived so as to be identified as multidimensionally poor. Name that cutoff as k. That k value can range from the weight of the least weighted dimensions to the total number of dimensions d.

Then, an identification function $\rho_k(y_i,z)$ is defined, such that:

$$\rho_k(y_i,z) = \begin{cases} 1 & \text{if } c_i \geq k \\ 0 & \text{if } c_i < k \end{cases}$$

That is, the identification function takes the value of 1 if the household is multidimensionally poor because the number of weighted deprivations is equal to or greater than k. If the number of weighted deprivations is less than k, household *i* is multidimensionally non-poor.

With the values from the identification function a column vector $p=[p_i]$ can be constructed, with $p_i=1$ or $p_i=0$ depending on whether household *i* was identified as poor or not. At this stage we have identified all multidimensionally poor households.

Once the poor households have been identified, it is possible to construct a censored column vector named $c_i(k)$ such that

$$c_i(k) = \begin{cases} c_i & \text{if } \rho_k(y_i,z)=1 \\ 0 & \text{otherwise} \end{cases}$$

From this vector one can obtain a simple 'score' (column) vector $s=[s_i]$ where $s_i=c_i(k)/d$ indicates the score of household *i*. In words, the score indicates the fraction of weighted dimensions in which each poor household is deprived. Note that there may be households experiencing deprivations, but with score zero because they have not been identified as multidimensionally poor.

It is also worth noting that by taking the mean of vector p, the *multidimensional headcount ratio* H is obtained ($H=\Sigma p_i/n$). Also, by taking the mean of the score vector s, the *adjusted headcount ratio M0* is obtained.

Our proposal is to use the identification function $\rho_k(y_i,z)$ as the targeting criterion for CCT programs and the score value s_i as a tool to prioritize among the households. H will indicate the proportion of beneficiary households and M0 will indicate the average proportion of weighted deprivations suffered by the beneficiaries.

Four properties of this identification methodology are worth noting which make it particularly suitable as a targeting criterion. In the first place, if a poor household's performance improves in a non-deprived dimension, this will not affect its identification as poor. In other words, a high achievement in one dimension cannot compensate for deprivation in other dimensions. For CCT targeting purposes, this means that eligibility is not affected by performances in dimensions not relevant for the program. This establishes a clear advantage of this method over the traditional unidimensional (proxy-means test) ones, which implicitly allow for substitution between dimensions. Secondly, if a household becomes deprived in one additional dimension, it may now fall into the group considered poor. For targeting purposes, that means that an increase in the number of deprivations directly increases the chances to become eligible for the program.[12] Third, this targeting criterion allows combining cardinal and ordinal well-being indicators, since all of them are dichotomized when establishing people's deprivations. Finally, the score vector s can be used to prioritize selected household if the CCT program must be implemented or expanded sequentially, from the most to the least deprived, or to tie transfer levels directly to the score (e.g., by increasing the benefits for those with lower scores and decreasing them for those with higher scores) with the purpose to improve the impact of the transfer on households' welfare (Coady and Parker, 2009).

[12] Alkire and Foster (2008) refer to the first property as "deprivation-focus" and to the second as "dimensional monotonicity".

Furthermore, the proposed targeting mechanism allows for a full consideration of the programs objectives, as one can define the dimensions in line with the objectives of the CCT. The traditional means-test considers only monetary poverty or the use a single cutoff point for well-being synthetic indices, leaving aside the human capital related dimensions: education and health-nutrition. Hence, the methodology allows for prioritizing dimensions when deciding the weighting as will be further discussed.

5. An application for urban *Oportunidades*

This section presents an illustration of how the new proposed methodology can be put in practice. Typically, CCT programs have intended to improve achievements in three dimensions: education, health-nutrition, and income. With the proposed multidimensional targeting, these dimensions can now be explicitly addressed and households experiencing coupled deprivations in these dimensions will receive a higher score and therefore, higher priority.

Although the selection of dimensions is actually determined by the program's objectives, the selection of indicators, deprivation cutoffs, weights, and across-dimensions cut-off opens a variety of possibilities. In all cases, choices need to be carefully justified as they will impact directly the target group. In what follows, we propose a specific selection for each case and we provide robustness checks for some of these choices. Clearly other combinations are also possible. It is worth emphasizing that two general criteria were followed in the selection of indicators. One of them is their availability in both the survey that determines the program eligibility as well as in the national household survey. All the proposed indicators are available on both the ENIGH 2006 and the ENCASURB (CCT urban census). The other general criterion intends to avoid the selection of indicators that may create negative incentives on the behavior of households (Coady *et al,* 2004b); such distortions are considered an important targeting cost (Paes de Barros and Carvalho, 2006). For example, if children not attending school was one of the indicators used by the program to select beneficiaries, this could create an incentive for households not to send their children to school in order to qualify for the program. All indicators related to the most immediate outcomes of the program are excluded from the models. Instead, we choose indicators that are highly correlated with the final indicators of interest, but are not subject to direct household manipulation (we refer to these as "intermediate indicators").

Proposed Indicators and cut-offs

Within each dimension we propose to include one *intermediate indicator* and, for the education and health dimensions, we also propose to include a number of *risks indicators*. Intermediate indicators are called as such because they are considered to be an effective means to an intended end of the CCT program. The intermediate indicator for education is grade retention of children aged 6 to 12, and a household is considered deprived if it has at least one child in this age group who is two or more grades behind in the school calendar. We base this selection on CONEVAL 2008. The intermediate indicator for health is access to health insurance. A household is considered deprived if at least one member does not have access to health insurance from institutions such as IMSS, ISSSTE, PEMEX, Popular Insurance, among others. Finally, the intermediate indicator for the monetary dimension is the per capita household income, and a household is considered deprived if it suffers economic poverty, that is, has insufficient income to afford basic needs. We estimate income using the projections of an income regression model (see Appendix A) and a cutoff that reproduces the official poverty ('capability poverty') rate at the household level stated by CONEVAL 2007.

Risk indicators included in the education and health dimension intend to capture the probability or vulnerability that households could suffer deprivations in these dimensions. By including such indicators, the program would benefit currently deprived households as well as households that have a high risk of becoming deprived. Given that CCT programs have special interest in improving the conditions of the young population, we consider that the selection of risk indicators should draw from empirical evidence on the causes of child malnutrition and school performance.[13] By focusing on the causes rather than the observable symptoms of such

[13] In the framework of these models, the urban-rural differences are captured through the characteristics of the places where the households reside, which play a relevant role for understanding individual behavior. The conceptual schemes for those models can be found in UNICEF 1998 and World Bank 2004.

phenomena, the effects of CCT programs would be more likely to last over time and avoid negative incentives. For example, child malnutrition could be reversed by attacking its most obvious manifestations, but this may have only temporary effects if they disappear. Actions to address causes, such as those that improve maternal nutritional knowledge, could have lasting effects or long term (Appoh and Krekling, 2005).

The literature for Mexico (Hernández *et al* 2003; Gómez 2003; González *et al* 2007; World Bank – SEDESOL 2008) finds evidence that malnutrition is basically related to the quantity and quality of food consumption, which are in turn determined by socioeconomic and demographic conditions. Specifically, the education of the mother and other family members, the presence of young children, a high concentration of indigenous people, the supply of and access to health services, and sanitary conditions in the house are all closely related to child malnutrition levels and household health in general. Regarding school performance (or lack of it, i.e. under-education), the literature indicates the importance of the following: economic poverty, parents' education, cumulative schooling as a function of age, presence of minor children, and factors of educational supply (such as availability of trained teachers and educational infrastructure), in addition to child malnutrition itself and neighborhood characteristics (López 2004; Muñiz 2001; Giorguli 2002). A revision of the conceptual and empirical discussions on these topics is beyond the scope of this paper. However, we argue that the selection of indicators to be used in the targeting mechanism should draw from the results this literature provides.[14] Combining such results with the availability of indicators in the two relevant surveys (ENIGH 2006 and ENCASURB) we selected ten risk indicators.

All the 13 selected indicators (three intermediate and ten risk ones) are listed in Table 1.2 and the dimension to which they correspond is indicated. It is noteworthy that some indicators are present in more than one dimension. Seven indicators are associated with the education dimension; ten are associated with the health-nutrition dimension; and only one with the monetary dimension. We considered the indicator on the educational level of other household members to be related to the health/nutrition dimension according to UNICEF 2009 and World

[14] UNICEF 1998 (Figure 5) shows an example of how complex it can be taken into account the diversity of the causes of child malnutrition to assess nutritional status and identify the most appropriate mix of actions.

Bank - SEDESOL 2008. The rationale is that more educated members of the household are more able to value nutritional foods and help with sensible intra-family sharing of foods and nutrients in favor of women and children.[15] The table also provides the deprivation cut-offs for each dimension as well as the formula used to define the weights, which are explained in the following section.

Weightings of dimensions and indicators

Determining the weights of each indicator is always an arbitrary decision. The literature indicates that selection should ideally be open to criticism so that it can gain reasonable public acceptance, since there are no universal guidelines for defining them.[16] It also indicates that any weighting scheme should be accepted if consistent with the trade-offs that exist between the dimensions. Because there is no consensus in how to measure these trade-offs, Decancq and Lugo (2008) have suggested to use common sense and be cautious in interpreting the rankings obtained from the group of dimensions. We propose giving the same weight to each dimension (education, health-nutrition, and income) and different weights for each deprivation (or indicator) according to its participation in each dimension. The formula used for obtaining these weights is presented in Table 1.2. Robustness exercises are conducted to analyze the sensitivity of the results to different weighting alternatives.

The dual cut-off: Minimum number of deprivations

As explained in Section 2, one of the advantages of Alkire and Foster's methodology is that it allows for a range of identification criterion from the union to the intersection approach. When indicators are not equally weighted, the union approach corresponds to being deprived in the indicator that has the lowest weight (k equals the weight of such indicator in this case). However,

[15] In the education dimension, the mother's schooling and the other school aged members' education are considered to influence the school performance of a child directly. For this reason, according to cited literature, the other household members' education was not considered.
[16] On this issue, the alternatives cited by Alkire and Foster 2008 for multidimensional poverty measurement include arbitrary weights and statistical weights (with factor analysis and multiple correspondence) based on surveys, value judgments, or some combination of these alternatives.

this criterion usually gives high poverty rates, especially when the total number of indicators is high. Indeed, such estimates may include households that happen to be deprived in just one indicator (even the least relevant) for other reasons than poverty. On the other extreme, when the intersection approach is used, households are required to be deprived in all considered indicators. This criterion usually leads to a very low poverty rate, including only the extremely poor households, who are deprived in all dimensions. Therefore, the extremes might not be useful to identify and target beneficiaries, and intermediate cases can be more relevant.

In the context of the CCT programs, one alternative for defining "minimum deprivations" is to determine it as function of the program's desired scope (in terms of the number of beneficiaries), budget availability, and also matching the official poverty measurement. The fact that the k value can be in an ample range, allows selecting the value that suits the mentioned three criteria. Figure 1.1 presents the estimated fraction of the beneficiary population (households with multiple deprivations) of the urban *Oportunidades* program for each possible minimum of deprivation – the second cutoff, k—, ranking from the minimum possible value of zero to the maximum of 13, since 13 indicators are used. The thick bold line depicts the results obtained with the mentioned weighting system, and the other two depict results with two alternative weighting systems: first, a set of weights in which the income dimension receives 30% more weight and alternatively, another in which it receives 30% less weight with respect to the baseline weighting structure. It is noteworthy that when the three lines overlap, it means that the fraction of the population identified as poor (i.e. as beneficiaries of the program) is independent of the weighting system used. This occurs in the neighborhood of k=7 and produces a poverty estimate of about 11 percent. It is worth noting that this estimate is coincident with the income poverty rate of 2006.[17]

6. Is the multidimensional targeting better?

A natural question that arises is how the proposed new multidimensional targeting method performs as compared to the existing ones. This section compares the performance of alternative

[17] The proposal and results are consistent with the suggestion made by Alkire and Foster 2008 that repeated applications and reasonable evaluations can lead to a range of plausible values for "minimum deprivations" and a single value can then be selected for the main analysis and alternative values to check its robustness.

targeting models and evaluates the relative performances with three techniques. As previously discussed, household targeting models commonly used by CCT programs focus primarily on the monetary dimension and the evaluation techniques traditionally used to assess targeting effectiveness are in this line. We aim at comparing beyond the monetary dimension by using alternative techniques to access if the proposed multidimensional model selects beneficiaries with deprivations in the dimensions relevant to the CCTs. In the first place, we analyze the distribution and coverage of the selected households by each targeting model along quintiles of the income distribution; this is a traditional way to evaluate the unidimensional targeting performance of beneficiary identification. Secondly, we compare household characteristics of the potential beneficiaries selected by each targeting model. Two indicators that are relevant for CCT programs are considered and average values of the indicators are compared along the cumulative distribution of household income poverty. Third, we use a micro-simulation technique to ex-ante evaluate the expected impact of transfers on school attendance and labor participation for children selected with each targeting model.

We compare the targeting performance of the following household identification models: (1) the current *Oportunidades* model (current SUP) which is the model that officially selects beneficiaries of *Oportunidades*, (2) the updated *Oportunidades* model, which we estimate using the same variables and methodology currently used in the SUP model, but consider recent survey data (updated SUP), (3) an alternative income proxy means that we estimate with ordinary least squares (income proxy), and (4) our proposed multidimensional targeting model.

In order to estimate the weights of all models we use information from the ENIGH 2006, with the exception of the current SUP (the current *Oportunidades* model) which uses the information from ENIGH 2000. It is worth noting that a household is eligible for the program according to the SUP models if the estimated score exceeds a given cut-off point; while according to the income proxy-means test a household is eligible if its estimated income is below a minimum income level or poverty line; finally, according to the multidimensional model, a household is eligible if it suffers at least a given minimum number of deprivations. The weights are available in table 1.2 (the multidimensional model) and Appendix A (SUP and income models).

Distribution and coverage: targeting performance according to the monetary dimension

This sub-section analyzes the performance of the four targeting models through a monetary lens. We define "distribution" as the number of eligible households in each quintile expressed as a percent of total eligible households in all quintiles and "coverage" as the number of eligible households in a quintile expressed as a percent of total households in the quintile under consideration. The higher the percentage of each indicator in the lowest quintile, the better the targeting performance of the method analyzed. A greater percentage of eligible households in the lowest income quintile indicate that the targeting model has performed well in identifying the income poor.

Table 1.3 shows the distribution and coverage of the selected households by the alternative targeting models in each income quintile. The comparison is carried out considering the poorest 10 percent selected by each model (for the case of multidimensional model it implied using k=7.4). This adjustment is necessary to fairly compare the four alternatives given that each model is likely to select a different number of beneficiaries. Regarding the "distribution", note that 70 percent of the selected households with the income and multidimensional models are in the poorest quintile, 8 percentage points higher than the current SUP and 5 percentage points higher than the updated SUP. It is also noted that both SUP models show higher percentages in the richest 40 percent of the distribution (first two quintiles)—leakage error, that is, non-poor households selected to receive *Oportunidades*.

The models' performance is somewhat comparable with respect to coverage in the different quintiles. While none of the models is able to cover half the lowest quintile, all models are pro-poor—with more coverage in the first quintile of the distribution. The main conclusion from this analysis is that the multidimensional model selected households with lower targeting errors than the SUP models and has a similar performance (about the same proportion of targeting errors) to the income model. The latter result is surprisingly good because the multidimensional model, unlike income models that consider only the monetary dimension of poverty, takes into account other key dimensions of CCT programs. Consequently, the profile of selected households with these two methods is different and is the focus of the next subsection.

Targeting performance beyond the monetary dimension

As the CCT program aims at the income poor that under invest in children's human capital (its target population), we propose to use indicators related to the investment in children's human capital to analyze the targeting performance beyond the monetary dimension. Child labor and school attendance are two of the indicators considered.[18] We profile the selected group of beneficiaries by each alternative targeting model. Figure 1.2 shows the average values of two indicators for different levels of cumulative household poverty (poverty defined according to the scores of each method). The dominance of the multidimensional model in identifying the most deprived households is clear, particularly in the lower levels of the welfare distribution.[19] For example, consider the indicator that aims at capturing households that are not investing in education: the school non-attendance of the poorest 15 percent selected with the multidimensional model is 42 percent higher than the non attendance of the poorest according to the updated SUP model and 9 percent higher according to the income model. Similar performance is observed for child labor. For the same population group and targeting models, percentages are 44 and 12 percent, respectively. It is noteworthy that differences are much larger if one consider the poorest 5 percent.

Ex-ante evaluation of CCTs: Is it worth changing the targeting strategy?

One final way to compare targeting models is by quantifying the potential impact of the program transfers on the children's occupational choice. While this is an unorthodox way of evaluating a targeting strategy, it goes beyond the simple analysis on the accuracy of predicting monetary or multidimensional poverty status of households. We use ex-ante microsimulation techniques, i.e.

[18] Due to the limited thematic coverage of the data sources used we restrict the analysis to these two indicators, but ideally should use indicators that account for outcome or impact indicators of CCT programs.
[19] In the case of multidimensional model, results for each percentile meant to use different levels of k (between 3.4 and 9.5).

methods designed to predict the impact of a program using behavioral models, which are estimated using econometric techniques at individual unit level (Todd and Wolpin, 2007). We model a discrete choice variable that expresses the labor participation and school attendance of a child. For this purpose, following Bourguignon *et al* 2003 and Chapter 2 in this dissertation, we assume that adults in the household decide on the occupational choice of the child based on a utility function, which depends on the characteristics of the child and of the household, education supply, and also the child's potential labor income.[20]

The models are estimated using information from the ENIGH 2006 and the *Oportunidades* scheme of transfers in place during the second half of 2006. We excluded from the sample all households that were beneficiaries of the program to avoid any bias in the estimation process; the final sample size used is still fairly large since 93 percent of the urban household total sample is not beneficiaries of *Oportunidades*.

Table 1.4 summarizes the results of the exercise. It shows the variation of transfers' impact on school enrollment and child labor participation, i.e. the difference between the situation before and after the *Oportunidades* transfers. The results are shown for the 5 percent and 15 percent poorest households selected with each targeting model. Note that for the poorest 15 percent, the *Oportunidades* transfers generate an increase in school attendance 54 percent greater if households are selected through multidimensional targeting compared to the current SUP model (8.5 percent versus 5.5 percent for children aged 9-18 years) and 16 percent greater than the alternative income model (8.5 versus 7.3 percent). For the 5 percent poorest (or extremely poor), the multidimensional model performance is superior to all other models under analyses in increasing school attendance and reducing child labor, particularly for children between 16 and 18 years of age.[21] This is in line with our priors since the multidimensional model explicitly considers the many dimensions of poverty and is better at identifying households that suffer deprivations and risks. Finally, Graph 1.3 compares the expected impact on school attendance if

[20] Appendix B contains model specifications and econometric details. For details on the methodology see Chapter 2 on this dissertation and Bourguignon et al (2003) for Brazil.
[21] The results of the analysis in this section are robust in the sense that they did not suffer significant changes when other weights were used in the multidimensional model (see graph 1.3).

beneficiaries are selected with alternative targeting models. The multidimensional model considers different weighting schemes; the results are robust with the multidimensional targeting alternative having a greater impact on school attendance for poor households.

7. Concluding remarks

This paper proposes a model for targeting beneficiaries of CCT programs that takes into account the two criteria that defines the target population of CCT programs: poverty and under-investment in human capital. The selection of indicators is in line with results of studies on the determinants of child malnutrition and school performance and the model is based on the axiomatic approach of multidimensional poverty measurement (Alkire and Foster 2008). We illustrate the proposed model for the case of the Mexican CCT *Oportunidades*. After building the identification function and a deprivation score using the information from the nationally representative Mexican household survey, we show that it is feasible to select households with attributes that better fit the objectives of a CCT program. Moreover, using ex-ante evaluation microsimulation techniques, the paper shows that a selection based on a multidimensional approach achieves a greater impact of transfers on the welfare of beneficiaries when compared to a targeting mechanism based on traditional approaches.

The implications of these findings should be considered in light of both equity and efficiency arguments. The reduction of targeting errors implies the possibility of a better use of public resources dedicated to social programs because resources will more effectively reach households with multiple deprivations. In addition, the proposed targeting model increases the impact of public resources, because the transfers would be given to households that have on average more deprivations, leading to a more efficient use of program resources. Thus, a change in the methodology to select beneficiaries is likely to contribute to achieving the fundamental objectives of CCT programs, particularly developing the human capital of children.

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Table 1.1: Descriptive Statistics: Variables of the *Oportunidades* current targeting model, SUP (2000 – 2006)

	Urban Area				Rural Area			
	Average		Correlation[1]		Average		Correlation[1]	
Variables	2000	2006	2000	2006	2000	2006	2000	2006
Age of the household head	45.2	46.5	-0.050*	-0.012	48.3	48.0	-0.065*	0.017
Female head of household (%)	19.6	26.1	-0.042*	0.024	16.2	23.1	-0.070*	-0.015
Households with children aged 0-11 (%)	97.2	85.9	0.323*	0.191*	133.8	116.2	0.381*	0.258*
Head of household with 0 years of education (%)	7.9	5.6	0.127*	0.144*	26.7	18.2	0.129*	0.155*
Head of household with 1-5 years of education (%)	16.7	13.9	0.153*	0.067*	33.2	32.3	0.086*	0.043*
Does not have access/right to medical service (%)	43.4	44.7	0.193*	0.173*	79.8	77.7	0.263*	0.207*
Demographic dependency (%)	72.0	69.3	0.291*	0.194*	98.8	96.9	0.312*	0.247*
Crowding: # of members / # of rooms	2.2	1.6	0.400*	0.274*	3.2	2.3	0.487*	0.324*
Dwelling with dirt floor (%)	2.4	2.5	0.168*	0.144*	22.3	15.4	0.343*	0.251*
Dwelling with shared or no bathroom (%)	7.0	5.4	0.075*	0.127*	23.3	15.6	0.183*	0.129*
Dw. w/unshared bathroom w/ no water conn. (%)	14.4	15.8	0.237*	0.173*	20.6	48.7	-0.063*	0.107*
Household without car or truck (%)	60.2	52.3	0.192*	0.16*	79.3	69.9	0.234*	0.194*
Household without gas stove (%)	3.0	5.0	0.071*	0.109*	27.6	22.7	0.407*	0.344*
Household without refrigerator (%)	14.2	11.2	0.278*	0.205*	47.1	35.4	0.385*	0.278*
Household without washing machine (%)	34.3	24.7	0.196*	0.186*	69.1	54.3	0.314*	0.249*

[1] Bi-variable with capability poverty

* Significant at 1%. On average, 26% less correlation with capability poverty in 2006 compared to 2000 in the rural area and 27% in the urban area.

Source: Calculations based on the 2000 y 2006 ENIGH.

Table 1.2: Dimensions, deprivations and weighting

Deprivations at household level (1)	Dimensions			Description	Weights of indicators in each in each dimension						Total weight each indicator (2)	
	Edu-cation	Health / Nutrition	Mone-tary		Edu-cation		Health / Nutrition		Mone-tary		Sum	d=13
Grade retention of members aged 6 - 12	X			At least one member with 2 or more grades below the age corresponding level (3)	0.14	+	0.00	+	0.0	=	0.14	0.619
Low education of members aged 16-21	X			At least one member with less than 9 years of schooling (4)	0.14	+	0.00	+	0.0	=	0.14	0.619
Low schooling of spouse	X	X		Spouse with less than 9 years of schooling (4)	0.14	+	0.10	+	0.0	=	0.24	1.052
Number of young children	X	X		Households with 3 or more children aged 0-11 (6)	0.14	+	0.10	+	0.0	=	0.24	1.052
Economic poverty	X	X	X	Insufficient income to afford basic consumption basket (5)	0.14	+	0.10	+	1.0	=	1.24	5.386
% Indigenous in the municipality of resid	X	X		% Indigenous people above the median (7)	0.14	+	0.10	+	0.0	=	0.24	1.052
# Schools in the municipality of residence	X			# primary and secondary schools below the median (8)	0.14	+	0.00	+	0.0	=	0.14	0.619
No affiliation to health insurance		X		At least one member without affiliation to any health insurance	0.00	+	0.10	+	0.0	=	0.10	0.433
Low education of other hh members		X		Older than 21 with less than 9 years of schooling (4)	0.00	+	0.10	+	0.0	=	0.10	0.433
Dwelling without piped water		X		Without public water inside or outside the home (inside or outside the home)	0.00	+	0.10	+	0.0	=	0.10	0.433
Dwelling without sanitary sewer		X		No sanitary sewer connected to public network	0.00	+	0.10	+	0.0	=	0.10	0.433
Households with overcrowding		X		# persons per room greater than or equal to 2.5 (9)	0.00	+	0.10	+	0.0	=	0.10	0.433
# Physicians in the residence municipality		X		# Physicians in contact with the patient below the median (10)	0.00	+	0.10	+	0.0	=	0.10	0.433
Total	7	10	1		1		1		1		3	13

(1) Defined with specific cutoff points for each indicator (see "Description" on this Table).

(2) Giving equal weights to each dimension and different weights to each indicator according to their participation in each dimension.

(3) According to the definition suggested in CONEVAL 2008.

(4) Corresponding to basic education as defined by the General Law of Education.

(5) Capability poverty, according to CONEVAL 2007. Income is estimated with the projections of a income regression model and a cutoff that reproduces the official poverty rates at the household level.

(6) The national median number of children is 2 per poor household.

(7) 1.90 percent is the median percentage in urban areas for capabilities poor households.

(8) 203 primary to upper secondary schools is the median in urban areas for capabilities poor households.

(9) Rooms counting the kitchen but not the bathroom. 2.5 is the cutoff point used by CONEVAL 2008 to define overcrowding.

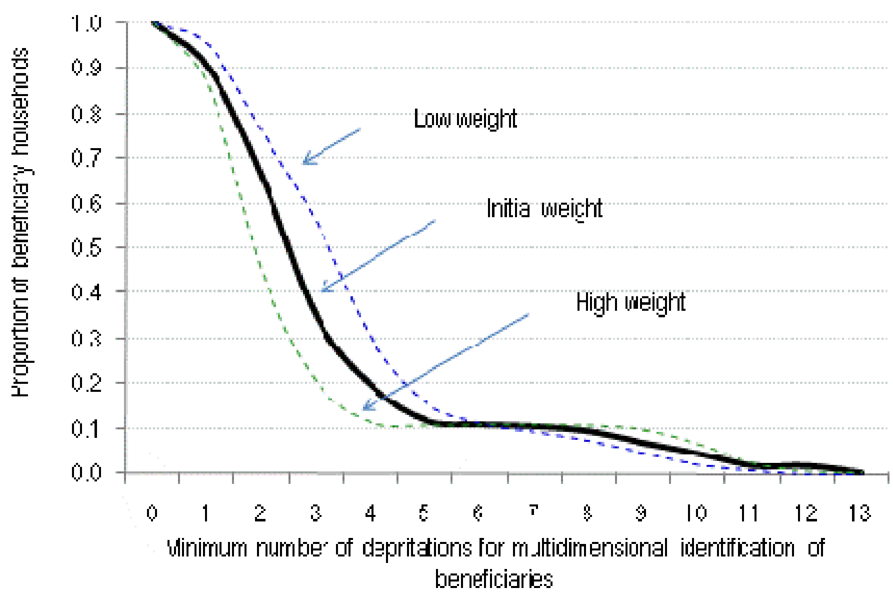
(10) 117 physicians is the median in urban areas for capabilities poor households.

Table 1.3: Distribution and coverage of potential beneficiaries (Urban areas)*

Model	Income quintile**					Total
	I	II	III	IV	V	
Distribution (%)						
Income proxy	70.4	22.1	5.7	1.7	0.1	100.0
Current SUP***	62.3	22.0	9.2	4.5	2.0	100.0
Updated SUP****	64.7	21.5	9.0	3.6	1.2	100.0
Multidimensional	69.2	22.8	5.9	2.0	0.1	100.0
Coverage (%)						
Income proxy	44.6	12.8	3.0	0.8	0.1	10.0
Current SUP	39.5	12.8	4.8	2.1	0.8	10.0
Updated SUP	40.9	12.5	4.7	1.7	0.5	10.0
Multidimensional	44.3	13.4	3.1	0.9	0.1	10.0

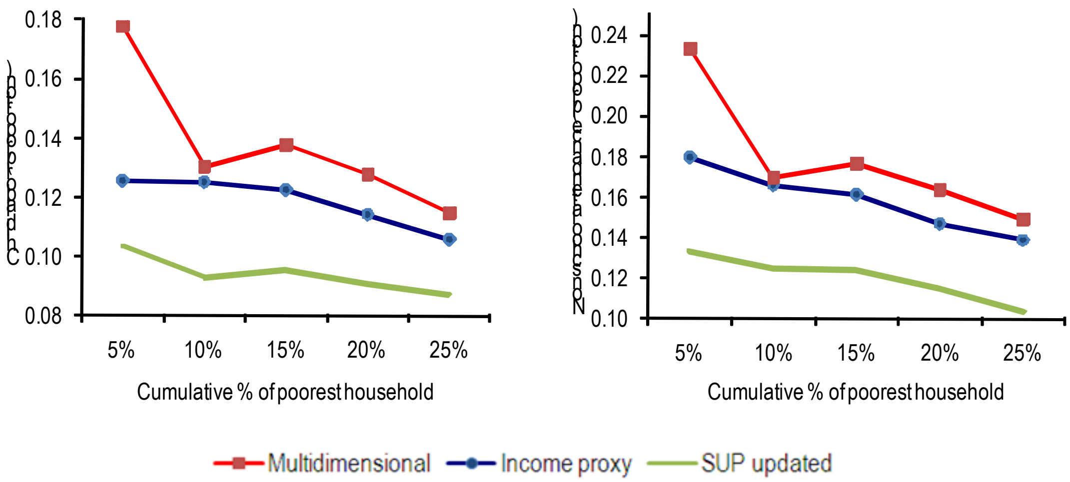
* selecting the 10% poorer household with each model.
** Five population groups of equal size based on per capita income (I poorer and V less poor).
*** weights calculated by *Oportunidades* with ENIGH 2000.
**** weights calculated with ENIGH 2006
Source: Author's calculation Based on ENIGH 2006

Graph 1.1:Proportion of urban beneficiary households for each minimum deprivations (Urban areas)



Initial Weight: consider the weights described in Table 2,
Low weight: 30% lower for monetary dimension with respect to the baseline (initial) weight structure
High weight: 30% higher for monetary dimension with respect to the baseline (initial) weight structure
Source: Author's calculation Based on ENIGH 2006

Graph 1.2:Child labor and Non-school attendance in household selected by three targeting models
(Urban areas)*



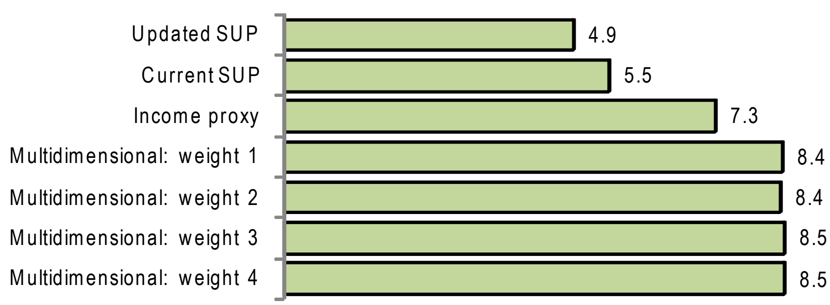
* Child labor and non-school attendance were estimated for members aged 12 – 17 years
The different levels of poverty (between 5 - 25 percent) were defined with each targeting models' score.
Source: Author's calculation based on ENIGH 2006

Table 1.4: Percentage change of the simulated impact of *Oportunidades'* transfers* on school attendance and labor force participation of poor children selected by four targeting models (Urban areas)

School attendance and labor force participation of children selected by alternative models	Poorest 5 percent				Poorest 15 percent			
	9-12	13-15	16-18	Total	9-12	13-15	16-18	Total
Observed								
No attending school	-29.9	-19.0	-15.2	-18.1	-22.0	-34.5	-24.1	-26.9
Attending school	1.9	6.6	32.0	6.0	0.8	8.4	33.3	6.9
Attending & working	0.0	0.0	0.0	0.0	0.0	0.0	5.6	1.9
Attending & not working	1.9	6.8	36.5	6.2	0.8	8.9	36.7	7.1
Income proxy								
No attending school	-11.2	-24.3	-10.7	-15.4	-17.6	-24.8	-21.2	-22.1
Attending school	0.7	11.6	37.2	6.1	0.7	7.9	44.4	7.3
Attending & working	0.0	0.0	0.0	0.0	0.0	0.0	7.0	2.7
Attending & not working	0.7	12.1	44.2	6.3	0.7	8.3	51.4	7.5
Current SUP								
No attending school	-9.1	-9.3	-12.7	-11.0	-21.1	-21.1	-19.1	-19.9
Attending school	0.7	4.0	57.6	3.9	0.8	7.1	44.3	5.5
Attending & working	0.0	0.0	0.0	0.0	0.0	0.0	9.7	2.8
Attending & not working	0.7	4.4	72.0	4.0	0.8	7.7	51.3	5.6
Updated SUP								
No attending school	-9.1	-10.1	-12.8	-11.4	-17.6	-18.1	-16.7	-17.3
Attending school	0.7	4.7	53.1	3.7	0.6	6.1	52.7	4.9
Attending & working	0.0	0.0	0.0	0.0	0.0	0.0	5.8	1.7
Attending & not working	0.7	5.1	63.1	3.9	0.6	6.7	67.6	5.0
Multidimensional model								
No attending school	-11.9	-17.5	-17.5	-17.1	-15.6	-27.2	-20.9	-22.2
Attending school	0.6	7.6	59.7	7.9	0.7	8.5	49.5	8.5
Attending & working	0.0	0.0	6.7	2.5	0.0	0.0	7.3	2.6
Attending & not working	0.7	8.1	71.3	8.1	0.7	9.1	56.2	8.7

* according to the *Oportunidades* scheme of transfers in the second half of 2006 (www.oportunidades.gob.mx/Wn_Inf_General/Padron_Liq/Mon_Apoyos)
NOTE: earnings and school attendance behavior models were considered for the simulations
Source: ENIGH 2006 (includes only urban households that are not beneficiaries of the program)

Graph 1.3: Simulated impact of the *Oportunidades'* transfers* on school attendance (percent change) of poor children aged 9-18 years old selected by four targeting models (Urban areas)



* according to the *Oportunidades* scheme of transfers in the second half of 2006 (www.oportunidades.gob.mx/Wn_Inf_General/Padron_Liq/Mon_Apoyos)
NOTE: school attendance behavior models were considered for the simulations
Weight 1: 15% for income and 85% for the other indicators
Weight 2: 29% for income and 71% for the other indicators
Weight 3: 41% for income and 69% for the other indicators
Weight 4: 77% for income and 33% for the other indicators
Source: ENIGH 2006 (includes only urban households that are not beneficiaries of the program)

Chapter Two
Ex-ante evaluation, simulations, and policy changes:
Is *Oportunidades* missing an opportunity?

1. Introduction

As stated in Chapter 1, Conditional Cash Transfers (CCT) programs have in general two main objectives: to alleviate poverty by raising the purchasing power of the household and to develop the human capital of children to break the intergenerational transmission of poverty. To achieve these objectives, cash transfers are given to the poorest households as in a social contract in which households commit to invest in children's education, health, and nutrition.[22] The education component of the program usually consists of a cash stipend that is conditional on school enrollment, attendance, and school performance.[23] The transfer amount covers part of the direct costs of attending school as well as the household's opportunity cost of sending children to school. The health and nutrition component requires preventive health care for children, regular health visits for pregnant and breastfeeding women and household participation in community informative meetings on nutrition and health care. The health and nutrition cash transfer aims to cover the cost of a basic food basket and health related needs. Designing and implementing conditional cash transfers often require accounting for country and region socio-economic indicators. For instance, if the conditionalities consist of school attendance and health check-ups, then the supply of schools and health clinics, the socio-economic indicators of the population, and the proportion of working children and adolescents have to be considered in the design of the program.

The Mexican CCT, first named PROGRESA and now *Oportunidades,* has been studied and evaluated by academics and policymakers. The program started in rural areas as a randomized

[22] Rawling and Rubio (2005) show the specific differences for six Latin American countries.
[23] Although these programs do not directly monitor school performance, evaluations show that performance is related to school attendance and the children's health and nutrition (Parker, Berman, and Todd (2005) and Todd et al. (2005)).

experiment, and because of that it offers a good benchmark for evaluation. The evaluations range from impacts on beneficiaries' consumption, health, nutrition, education, and migration patterns. A comprehensive assessment indicates that the *Oportunidades* program has been welfare enhancing in several dimensions as summarized by Levy (2006), Behrman et al. (2005), Schultz (2004), and Parker (2005). Although the impacts of the Mexican program are undoubtedly positive, structural modeling can shed light on the potential policy changes that can further enhance program outcomes.

The purpose of this paper is twofold. It assesses the Bourguignon, Ferreira and Leite (2003) model as an ex-ante evaluation microsimulation technique and analyzes the potential impacts of policy changes in the *Oportunidades* program on household behavior and welfare indicators. The first objective is accomplished by applying the Bourguignon, Ferreira and Leite (2003) model (henceforth BFL), which was first designed to analyze the Brazilian program, to the Mexican program. This paper relaxes the identifying assumption of the BFL model which overestimates the simulated impacts of the CCT transfers. The findings of this paper indicate that the BFL model can be used as an ex-ante evaluation technique. The model accurately predicts the school attendance outcomes of the *Oportunidades* program in 93.2 percent of the cases as we compare simulation results with household survey data.

The potential impact of policy changes are analyzed through simulations of the BFL model—the paper's second objective. The benchmark is the 2005 *Oportunidades* program rules, which are then modified to estimate the impact of changes in the program on school enrollment, poverty, and inequality. We use a Mexican household survey, which is representative at the national level prior to the launch of the program. Most of the related research uses the data collected to evaluate the program in rural areas, which is not representative at the national level.

Improving the effectiveness of the *Oportunidades* education conditionality and of other interventions to increase adolescent's school attendance is a policy priority for Mexico. In urban areas, only 78 percent of adolescents between 12 and 18 years old attend school. Evidence from Mexico's household surveys indicates that school dropout rates start to increase at age 14, while labor market participation also increases. This has important implications for program design, as it suggests there is scope for re-calibrating Program rules with the aim of increasing school enrollment among adolescents.

This paper is organized as follows. The next section reviews the related literature with a focus on the Mexican CCT and is followed by a brief description of the program. Section 4 describes the methodology and section 5 focuses on the empirical application. Finally, Sections 6 concludes.

2. Program evaluations: a brief review

Past research has shown that income transfers have been successful in improving health indicators, increasing school attendance, and reducing current poverty and inequality indicators. CCTs focus on poverty alleviation and household investment in human capital, primarily by increasing school enrollment. As with other successful policy interventions, policymakers and researchers alike have questioned the possibility of further efficiency gains by fine tuning the design of the program.

Impact evaluations are an important tool to measure program outcomes ex-post. The *Oportunidades* program was designed from the start to have a measurable impact. The program was implemented as a randomized experiment, and as such it offers a perfect benchmark for evaluation. The results of the short-run impact evaluations in rural areas are summarized in Skoufias (2005). Another valuable source is Levy (2006) who summarizes many impact evaluations of the Mexican program including consumption, health and nutrition, education, and targeting.

The assessed impact of the program on education indicators vary by educational level and socio-economic background.[24] According to Schultz (2000) the program's impact on primary school enrolment has been small and this might be due to the fact that primary school enrolment rate was already high (around 90%) when the program was implemented. This result is corroborated

[24] See also Behrman et al. (2005), Gomez de Leon and Parker (2000), Parker and Skoufias (2000).

by Parker (2003), whose research also indicated that the program affected dropout rates negatively (keeping students enrolled). Todd et al. (2005) also confirms this result for urban areas.

The scenario is very different if considering secondary education. Estimates of the increase in secondary education levels are around 11 percent for girls and 7.5 percent for boys in rural areas after just 2 years of the program (Schultz, 2000). Another study uncovers similar results: Parker (2005) finds a 24 percent increase in secondary school enrolment between the launching of the program and the 2002-2003 enrolment rates in rural areas. She indicates that the increase was higher for girls than for boys— 28.7 percent and 15.7 percent respectively. A study by Hernandez et al. (2000) finds that the program had a bigger impact on school attendance of children of less educated mothers. In schools where the average years of education of the mothers were low (around 3 years of education) school enrolment increased by 75 percent more than in schools where the average mothers' education was higher (around 9 years).

As described above, the evaluation results largely indicate that the program has had a stronger positive effect on secondary and high school enrolment. A study by Skoufias (2000) suggests increasing education transfers to students who finish high school and encourages establishing a relationship between the money allowance and school performance. As indicated by Levy (2006), the *Oportunidades* program increased the transfer to high school students (without linking it to school performance) in 2001. The results of Parker (2005), which analyses the impact of additional scholarships for high school students, indicate an increase of 85 percent in high school enrolment for rural areas and 10 percent for urban areas.

In order to design social programs or to fine-tune existing programs, researchers have increasingly turned to techniques that enable them to shed light on the potential impacts of policies. Ex-ante evaluation models include an array of possibilities and aim primarily at simulating the effects of policy interventions (before they take place) to quantify their impact. Finding a balance between the model's structural complexity and feasibility of an empirical application is the challenge for the achievement of a successful ex-ante evaluation. As mentioned by Wolpin (2007) there is no consensus of what constitutes the best model of ex-ante policy evaluation. The non-experimental approach, which is what defines an ex-ante evaluation of any policy intervention, must rely on parametric as well as behavioral assumptions.

For PROGRESA-Oportunidades, Todd and Wolpin (2006) estimate and validate a dynamic behavioral model of parental decisions about fertility and school attendance to evaluate the effects of the program. The authors carry out several counterfactual experiments of program rules and identify an alternative transfer scheme that could increase average school attendance without further increases in the program's budget. They compare their ex-ante results with the results found in ex-post evaluations of the program. Using the same data, Attanazio et al. (2001) analyze a dynamic school participation model and discuss an alternative program design that focuses on secondary school attainment. De Janvry and Sadoulet (2006) use the 1998 PROGRESA survey data to analyze efficiency gains—by means of improving school enrollment among poor children—in the program. Their paper proposes improving targeting among poor households and changing the design of the cash transfers.

As pointed out by Heckman (2000), the forecast of policy changes before their implementation is one of the greatest challenges of empirical research. Simulation exercises as well as ex-ante evaluations techniques are frequently implemented in the context of social programs (Freije et al., 2006; Todd and Wolpin, 2006 and 2007). More than a few surveys in the literature analyze the evolution and application of these techniques in different fields. BFL propose a behavioral ex-ante microsimulation methodology to assess the potential impact of alternative transfer schemes on the household decision to send a child to school. Their paper applies the methodology to the Brazilian Bolsa Escola program using data from a household survey. This paper applies the BFL model for the Mexican program and perform simulations of alternative designs of the transfers scheme to fine-tune the 2005 program rules. Bornhorst (2004) applies the BFL model to the evaluation data base of rural PROGRESA. In the same line as this work—with the objective of validating the BFL model—his findings indicate that the effects measured by the ex-post evaluation technique are within the confidence interval obtained through the microsimulations. However, his results are not representative at the national level and in the rural sample transition to secondary education is not captured well by the model.

3. Program Background and Description

For many decades Mexico had numerous social programs aimed at reducing poverty and improving inequality indicators, but the evolution of the indicators suggested that many of the programs did not attain its objectives. For instance, it is estimated that by the mid 1990s around 24 percent of the Mexican households lived in extreme poverty. In rural areas, more than half of the households lived in poverty. There are two main reasons why such programs were not successful. First, the programs were run independently of each other and many times replicated efforts. One example is the food subsidies; in the 1990s the Mexican government had fifteen food subsidy programs operated by ten different ministries. Second, most of the programs consisted of generalized subsidies with a large proportion of benefits being delivered to the non poor (households that were above official poverty lines). Targeting mechanisms were weak in urban areas and very limited in rural areas (Levy and Rodriguez, 2004).

The socio-economic conditions and the macroeconomic framework indicated that reform of the social sector was timely. During the first half of the 1990s, the Mexican economy suffered a setback and in December 1994 a major macroeconomic crisis drove per capita income down by around 6 percent during 1995; this was the major reduction in economic activity in more than fifty years. The necessity of a mechanism to support the poor then became a consensus among policymakers.[25]

PROGRESA was first implemented in 1997 in rural areas of Mexico. The program aims to break the vicious cycle of poverty by increasing children's human capital through investment in health, education, and improved nutrition rates. The specific objectives can be summarized as follows: (i) improve health and nutritional status of the poor households; (ii) promote school enrollment

[25] In the political context, President Zedillo was starting his term and the political climate facilitated the change in the direction of social policy See Levy (2006) for a very interesting description of the political process and background information on the program.

and completion at all levels; (iii) give more stability to extremely poor households by guaranteeing a minimum level of consumption as well as to redistribute income; (iv) integrate education, health, and nutrition interventions in order to improve school performance; (v) encourage responsibility and participation of all family members as well as improving the family's educational, health and nutritional status. This can be achieved by providing information on this issues and not interfering with family size, spending patterns, and child's education (Levy, 2006).

The program conveys cash to poor households under the condition that they engage in behaviors that are consistent with the accumulation of human capital. The largest transfer of the program is the educational one. Grants are paid to poor mothers (targeted trough a combination of geographical and proxy means testing) if their school-age children enroll and attend school regularly.[26] The cash transfers assigned to each household depend on its composition and characteristics. The program has three closely related components: education, health, and nutrition.

The educational grants consist of three parts. The first part requires every school-age child enrolled in the Program to attend at least 85 percent of the classes per month from the third grade of primary school to the end of secondary; the student then receives a scholarship for 10 months of each year. The transfer increases with the school year and is adjusted to avoid drop-outs; for example, the scholarship is higher for girls than for boys after secondary school. The second sub-component is a one-time cash transfer received upon high school completion. Finally, the third sub-component is related to school supplies. Primary school students receive two installments (at the beginning of the term and at half term) while secondary and high school students receive one installment upon registration.

The health-nutritional component (also called food component) has both cash transfers and in-kind benefits. All households receive the same monthly cash allowance. Additionally, pregnant

[26] For further details see Skoufias (2001); Skoufias and Parker (2001); Attanasio, Meghir and Santiago (2005), and Angelucci and Attanasio (2006), among others. This section pays special attention to 2005 as we will consider the reference year.

and nursing mothers, infants between four months and two years old receive an in-kind supplement. The benefits are conditional on attending regular health check-ups. The health component is closely linked to the nutritional component and is delivered when the households visit health clinics for the nutritional component.

As reported in Levy (2006) the program transfers represent around 25 percent of the household income for the rural poor and between 15-20 percent of urban household income. The education component represents around 50 percent of the transfer, the cash transfer for the nutritional component amounts to 36 percent and the in-kind transfer represents 4 percent. Finally, medicines and other health services provided constitute the remaining 10 percent. The program sets a maximum allowance on the amount of transfers to avoid adverse incentives on fertility; additionally some benefits are temporary to avoid reliance or dependence on the cash transfer. In 2005, our year of reference, the program benefited 5 million families with a cost of 24,617 million pesos (US$2.30 billion), and provided in-kind benefits of around 3,828 million pesos (or US$357 million). This amount to a direct monetary assistance of 4,923 pesos in cash (US$460) and 765 pesos in kind (US$71.40) per family per year, or 474 pesos (US$44.30) per family per month. According to the same source, these transfers are second in size only to those associated with social security.

The PROGRESA-Oportunidades program expanded rapidly during the 1997-2005 period. Implementation began in August 1997, with the incorporation of approximately 140,000 households into the program. By early 2000, the program included nearly 2.6 million families in 72,345 localities in all 31 Mexican states. As of the end of 2007 and the beginning of 2008, 5 million families were included in the program.

4. Methodology

This section adapts the methodology proposed by BFL which is based on micro-econometric estimations of models of household behavior. This paper relaxes the assumption that the observed labor allocations between market and domestic activities are corner solutions. As in

BFL, the empirical model makes four simplifying assumptions for the decision making process. First, the occupational choice model is a reduced form of the outcome resulting from an intra household decision of who attends school and who works. Second, adults make their own occupational choice decisions first and then decide upon the child's. Furthermore, adults' occupational choice does not affect the decision to send a child to school. Third, the model applies to all school-aged children, and it ignores any consideration of interactions with siblings' schooling decisions. Fourth, household composition and fertility decisions are exogenous.

Theoretical Model:

Educational choice

Decision makers in the household decide upon sending a child to school in order to maximize utility. The variable S_i is a qualitative variable representing the occupational choice made for a child in household i. This variable takes the following values:

S_i = 0 if the child does not attend school;
1 if the child attends school and *works* outside of the household;
2 if the child attends school and *does not work* outside of the household;

Assume that when $S_i = 0$ the child works full time either in the household or outside of it, and in the latter case receives a wage. Likewise, when $S_i = 2$ it is assumed that the child may be helping with household activities and attending school.[27] The occupational choice variable S_i model follows the standard utility-maximizing multinomial logit model, the model can be characterized by:

$$S_i = k \text{ iff } \quad S_k(A_i, X_i, H_i, Y_{-i}, y_{ik}) + v_{ik} > S_j(A_i, X_i, H_i, Y_{-i}, y_{ij}) + v_{ij} \text{ for } j \neq k \qquad (1)$$

[27] The assumption that all children not in school are working at home or in the market is definitely strong and might not be consistent with the data. Market and domestic wages are assigned (Mincerian prediction) to children not working to perform the simulations.

where $S_i()$ is a latent function that reflects the net utility of choosing alternative $S_i=k$ (=0, 1 or 2). Note that $S_i()$ is a function of child, household, labor market, and education supply variables for the child that affects the choice of the labor option j; A_i is the age of the child i; X_i is a vector of the child's characteristics (including its gender, number of siblings, birth order, variables related to past child educational attainment); H_i is a vector of the child's household characteristics (size, age and education of the parents, presence of siblings at school age, distance to school, etc.); Y_{-i} is total household income except for the child's income and y_{ij} is the child's own contribution to the household income. Finally, v_{ij} is a random variable that captures unobserved heterogeneity of the observed S_i choice.

Consider that all non-income explanatory variables (A_i, X_i, H_i.) are collapsed into a vector Z_i and assuming that $S_k()$ can be defined as a linear function, equation (1) becomes:

$$U_i(j) = S_j(A_{i,}, X_i, H_i; Y_{-I} + y_{ij}) + v_{ij} = Z_i.\gamma_j + (Y_{-i} + y_{ij})\alpha_j + v_{ij} \qquad (2)$$

where α and γ are the parameters to be estimated.

Finally, household's choice of k seeks to maximize the following function:

$$k^* = Arg\ max_j[Ui(j)] \qquad for\ all\ j = 0,1,2$$

where: $U_i(j) = S_j(A_{i,}, X_i, H_i; Y_{-I} + y_{ij}) + v_{ij}$

Estimating potential wages

The standard Mincerian earnings model (Mincer, 1974) is used to predict potential earnings for the children that do not report any market earnings, those working in the household and as well as a predictor of potential earnings arising from working part time while studying.

$$Log\ w_i = X_i\,\delta_j + m^*Ind\ (k=1) + u_i \qquad (3)$$

where w_i is the observed earnings of the working child; X_i is a set of individual characteristics (including age and years of schooling) and u_i is a random term that stands for unobserved earnings determinants, such as ability. Ind ( ) is an indicator function that equals one if the children both attend school and work outside of the household. This term accounts for the fact that the number of hours worked differs substantially between kids in occupational choices 0 and 1.

According to equation (3) the child's contribution to household income (y_{ij}) is defined as:

$$
\begin{aligned}
y_{i0} &= Kw_i && \text{for } k=0 \\
y_{i1} &= M\,y_{i0} = MKw_i && \text{for } k=1 \qquad\qquad (4)\\
y_{i2} &= D\,y_{i0} = DKw_i && \text{for } k=2 \qquad \text{with } M= Exp(m)
\end{aligned}
$$

The child's contribution is defined for $k=0$ as a proportion to actual or potential market earnings, w_i, in a proportion K for children who do not attend school. For $k=1$, the child works in the market and studies at the same time, spending less time in the labor market than the child in the category $k=0$, so they only receive a fraction M that corresponds to the time devoted to work of the observed market income w_i. The same argument applies for $S_i=2$ $(j=2)$ because the child can contribute to domestic production D.

Replacing equation (4) into (2) yields:

$$
\begin{aligned}
U_i(j) &= S_j(A_i, X_i, H_i; Y_{-i} + y_{ij}) + v_{ij} \qquad (5)\\
&= Z_i.\gamma_j + Y_{-i}\alpha_j + w_{ij}\beta_j + v_{ij}
\end{aligned}
$$

with $\beta_0=\alpha_0 K;\ \beta_1=\alpha_1 MK;\ \beta_2=\alpha_2 DK$

After knowing all coefficients (γ, α, β), as well as the actual or potential market earnings, and the residuals v_{ij}, the household decides on the child's occupational choice by maximizing the following function:

$$k^* = Arg\ max\ [Ui(j)] \tag{6}$$

This represents the utility function of the households without considering the conditional cash transfer program. Means-tested conditional cash transfers programs affect the utility function by an increase in household income of the size of the transfer, T. If the schooling conditionality is enforced, equation (5) becomes:

$$U_i(j) = Z_i.\gamma_j + (Y_{-i} + T_{ij})\alpha_j + y_i\beta_j + v_{ij} \text{ with } T_{i0}=0 \text{ and } T_{i1} = T_{i2} = T \tag{7}$$

Simulating Oportunidades: the household maximization utility problem

Taking into account the scheme of transfers in place in 2005 and the eligibility criteria based on the proxy means test, household i will choose j in order to maximize the following program specific alternatives:

$Ui(j) = Z_i.\gamma_j + Y_{-i}\alpha_j + y_i\beta_j + v_{ij}$ *if the household is "not poor", for j=0,1,2*

$Ui(j) = Z_i.\gamma_j + \alpha_j(Y_{-i} + A) + y_i\beta_j + v_{ij}$ *if the household is "poor", for j=0*

$Ui(j) = Z_i.\gamma_j + \alpha_j (Y_{-i} + A + B) + y_i\beta_j + v_{ij}$ *if the household is "poor", for j=1,2*

where A is the unconditional food transfer given to all household below the poverty line and B is the school transfer conditional on school attendance according to the grade, level and gender. With this reduced form model and the parameters (α, β, γ, y_i, and v_{ij}) one can simulate the impacts of changes in the design of the program.

Empirical considerations: the identifying assumption

The utility maximization problem is estimated using the standard multinomial logit framework. If v_{ij} is iid across sample observations with a double exponential distribution, the probability that household *i* will select the choice *k* is given by the multinomial logit function:

$$p_{ik} = \frac{Exp[Z_i\gamma_k + Y_{-i}\alpha_k + y_{ik}\beta_k]}{\sum_j Exp[Z_i\gamma_j + Y_{-i}\alpha_j + y_{ij}\beta_j]} \qquad (8)$$

For example, considering the choice *k=0* yields:

$$p_{ij} = \frac{Exp[Z_i(\gamma_j - \gamma_0) + Y_{-i}(\alpha_j - \alpha_0) + y_{ij}(\beta_j - \beta_0)]}{1 + \sum_{j=1}^{2} Exp[(Z_i(\gamma_j - \gamma_0) + Y_{-i}(\alpha_j - \alpha_0) + y_{ij}(\beta_j - \beta_0)]} \qquad (9)$$

and $p_{i0} = 1 - p_{i1} - p_{i2}$ for j=1,2.

Usual estimation of multinomial logit generates estimates of the differences (α_j-α_0), (β_j-β_0), and (γ_j-γ_0) for j=1, 2 (j=0 is the reference). Because income variables are asymmetric across occupational alternatives, this is insufficient and it is necessary to know all three coefficients (α_0, α_1 and α_2) in order to identify the utility maximizing alternative k*.

Let *a* and *b* be the estimated coefficients of the multinomial logit corresponding to the income and the child earning variables for alternatives j=1, 2 and as before the alternative 0 is the reference category. From equation (5), the following system of equation arises:

$$\begin{aligned} &\alpha_1 - \alpha_0 = a_1 \\ &\alpha_2 - \alpha_0 = a_2 \\ &(\alpha_1 M - \alpha_0)\, K = b_1 \\ &(\alpha_2 D - \alpha_0)\, K = b_2 \end{aligned} \qquad (10)$$

The above system of equations contains 4 equations and 5 unknowns ($\alpha_{0,}$ $\alpha_{1,}$ α_2 K and D). The value of M is known from equation 3. BFL point out that "arbitrarily setting" a value of K or D allows the identification of the remaining parameters and they set K=1. This paper proposes the estimation of K from the household survey. The equations that follow do not assume K=1 being different from the ones in the BFL paper, since as in equation (4) child's domestic income contribution is proportional to actual or potential market earnings K (= y_{i0}/w_i). In this case, it follows that:

$$\alpha_0=(\alpha_1-a_1);\ \alpha_1 = [a_1-(b_1/K)]/(1-M);\ \alpha_2=(\alpha_1+a_2-a_1);\ D=(b_2+\alpha_0 K)/(\alpha_2 K) \qquad (11)$$

In a discrete choice model, the residual terms are within certain known boundaries but are not observed. The term v_{ij} - v_{i0} needs to be drawn for each observation in the relevant interval to satisfy the selected choice. For example, if household *i* selected choice 1 (k=1), then it must be the case that

$$Z_i\gamma_j + Y_{-i}a_1 + b_1 w_j + (v_{i1} - v_{i0}) > Sup\ [0, Z_i\gamma_2 + Y_{-i}a_2 + b_2 w_i + (v_{i2} - v_{i0})]$$

The term $(v_{i1} - v_{i0})$ should satisfy this inequality.

which can be achieved if one takes into account the following rules:

v_{ik} = -ln[-p_{ik}*ln()] if j=k
v_{ij} = -ln[exp(-v_{ik})*(p_{ij}/p_{ik})-ln()] if $j \neq k$

where () = uniform(), a function that produces uniformly distributed random numbers for the interval [0,1).

5. Data and Results

Data

The data base consists of the nationally representative Mexican Household Income and Expenditure Survey— ENIGH (Encuesta Nacional de Ingresos y Gastos de los Hogares) for 1996 and 2005. The survey provides socio-economic information at individual and household level. The program rules and detailed data on the transfer amounts and budget are from the Mexican government.[28] Table 2.1 summarizes *Oportunidades* educational transfer levels by grade and gender in place in 2005. The nutritional transfer in 2005 corresponded to 170 pesos and is given to all poor households. Poor households are defined according to the program's rule: all households that have a living condition index below the cut-off point (for details refer to Chapter 1, Section 3).

Descriptive statistics

Considering all children aged 7 to 18 years old in 1996, around 74 percent attended school and did not report to be working on the market; four percent were both enrolled in school and working in the market while 21 percent were not attending school, as presented in table 2.2. Note that the average values conceal a great amount of variation across ages—on average most 11 year old children attended school (96%) and only around 3.5 percent did not attend school. School attendance diminishes with age while the number of working children increases considerably. At the age of 16, around 47 percent of the children devote their time to attending school only meanwhile around 45 percent did not enroll in school and 7.2 percent attend school and work at the same time. National data in the year 2005 indicates that school attendance have increased for all age groups—which might reflect the effects of the CCT program. It is noteworthy a reduction in child labor for children aged 12 and 13 of more than a percentage point.

Table 2.3 describes the sample mean of individual and household characteristics of the children aged 12 to 18 by occupational category for 1996 and 2005. It also contains the variables that proxy for the supply of schools such as the distance to the closest school and the number of

[28] Data on the supply of schools was provided by the "Dirección General de Planeación y Evaluación de la Coordinación Nacional del Programa de Desarrollo Humano Oportunidades".

students per teacher.[29] Children who are not attending school are on average older and less educated than those who attend school (or attend school and work). It also the case that children who are out of school or attend school and work are from households with lower income levels, their parents have on average less education, and are more prone to live in rural areas and have more siblings younger than five years old. There are a higher proportion of out-of-school children in the center-west, center and south-southeast areas of Mexico when compared to the northeast and northwest areas.

A noteworthy statistic of table 2.3 is the reported wage income of children aged 12-18. Note that the reported earnings of the out-of-school children are a significant source of household income. In 1996 it accounts on average for about 7 percent of total income and in 2005 it represents almost 10 percent. The amount of children's contributions (wage income) is significantly higher for 2005 and notably below the transfers provided by the program. Regarding the supply of schools, there is a clear improvement of the indicators. Note that there is a reduction in the average distance between the center of the neighborhood where the household is located and the school.

[29] This indicates school availability and is considered in the multinomial logit estimation. We are aware of the limitations of using these indicators to proxy school quality or investment in education as discussed in Glewwe (2002); the idea here is to proxy for availability of schools only. The data is available at the state level form the website: http://www.sep.gob.mx/wb/sep1/sep1_Estadisticas

A closer look at school enrolment

Table 2.4 describes school enrollment and occupation choices of children by age groups for 1996 and 2005. School attendance has increased for the poor and non-poor groups of the population in the period under consideration. Primary education attainment is almost universal in Mexico, but considering all children aged 9-11 the number of children not attending school decreased from 3.3 percent to 1.7 percent in the period 1996-2005. For the age group 12-15 years old, the reduction in the out-of-school group was from 21 percent to 13 percent in the period under consideration. For the older children, those included in the group 16-18 years old, the percentage of youth not attending school decreases by ten percentage points in the period from 56.2 percent to 46.8 percent. Improvements in school attendance are more pronounced for poor children. Not surprisingly, the percentage of children not attending school is higher for poor children in all age groups. For example, in 1996 an astonishing 79 percent of the poor children between 16 to 18 years old were not attending school; in 2005, school enrollment for the same age group had increased by more than 10 percentage points. The graphs in the appendix provide detailed information on school attendance for all kids aged 6-18. Finally, Table 2.4 also indicates that the program has had a smaller effect on the group of children who are both in school and working. It reflects the fact that the program has a limited income effect on child labor, and that most of the effect operates through the substitution effect (which, indeed, is irrelevant to enrolled children, even if they are working). Later we show that this behavior persists when we simulate the effect of different transfer schemes.

Model estimation

Earnings

The earnings of a child are likely to affect the household decision of sending this child to school. The survey provides information for all children working in the market and receiving a wage; the wages of all other children have to be estimated. Table 2.5 reports the results of the ordinary least squares estimation of the earnings equation.[30] The equation is estimated for all children aged 12 to 18 (reported below) as well as for urban and rural areas separately (Appendix C). We also consider using a proxy of low-skilled adult workers instead of child earnings as in Duryea and Arends-Kuenning (2003).[31] Even though the results are similar, considering the hourly wages of low skilled male workers produce high potential earnings because in Mexico the average wage of unskilled male workers are much higher than those of children.

Consistent with most results for the Mincerian equations age and years of education positively affect the wage (Heckman and Todd, 2006). The results indicated that as the child gets older the wage increases. An additional year of age increases wages by 14 percent while an additional year of education increases wages by one percent. The dummy variable for males is also positive and significant while the dummy for rural areas is not significant. In previous estimations all regional dummies were also insignificant and were dropped without affecting the results. The variable school-age gap is a dummy variable that is equal to one if the schooling of children is lower for their age and zero otherwise. This variable also has the expected sign (the probability that the children work is higher if they have a school-age gap) and is significant. The log of the median wage, which serves as a proxy for the labor supply, is also positive and statistically significant.

The dummy variable "works and studies" in table 2.5 is the estimated coefficient for the parameter M. As expected the coefficient is negative indicating that a child that attends school and works in the market reduces total earnings when compared to a child with similar characteristics that devotes time only to work. This coefficient reflects that a child going to school works on average 41 percent less than a drop out. The estimates for urban and rural areas indicate that a child attending school works 25 percent less than a drop out in urban areas and 58 percent less in rural areas (Appendix C).

[30] Unlike BFL this paper estimates one Mincer equation due to sample size restrictions.

[31] We also took in consideration sample selection bias. Although we did not find evidence of selectivity, this estimation is problematic given the restricted number of available instruments that affect earnings but does not influence the occupational choice decision.

The coefficient of the log of median wage is positive and statistically significant. This variable is constructed as the median of the distribution of earnings by state. It can be interpreted as a proxy for the geographical demand for child labor as it reflects the price of child labor and affects the child occupational decision through potential earnings. As indicated in BFL this is an identifying instrument and is not included in the multinomial logit estimation.

Occupational choice

The results for the marginal effects (elasticities calculated at the means of the independent variables) and p-values of the multinomial logit estimation are reported in table 2.6; taking as reference the category is that the child is not attending school. We tested for the independence of irrelevant alternatives, indicating that all choices (probabilities) are independents according to the results of Haussman-McFadden test and the Small-Hsiao test (Appendix E). Total household income, net of the child's income contribution, has a positive and very small effect on the schooling decision. The child's predicted earnings reduce the probability of working and studying, compared with the alternatives. Previous education and years of education have a positive effect on the probability of studying. Parents' education has a negative effect on the probability of working and studying as well as a positive effect on the probability of studying only. The variables related to the school supply affect positively the probability of studying and working. Boys are more likely to study and work at the same time than girls. Children in the rural area are less likely to work and attend school than those in urban areas. Appendix D in the appendix displays the coefficients (instead of the marginal effects) of the multinomial logit presented in Table 2.6 as well as an alternative estimation that considers the education level of the parents instead of years of education.

The estimated parameters are in line with the theoretical model. The values of α_1 and α_2 are positive and very small.[32] The value of the parameter D (D =1) indicates that children who are in school and do not work outside the household are estimated to provide domestic production for

[32] The values of α_1 and α_2 are calculated using the system of equations (10). The values are calculated directly from the multinomial model estimated (equation 9) and not from the above table, which contain marginal effects from the estimated multinomial.

about the same value of their potential market earnings. The value of D being greater than M indicates that the contribution to domestic activities of the children that study only is on average greater than the contributions from those study and work, as expected. K is estimated from the survey for rural and urban areas separately and has an average value of 1.39. The remaining parameters are α_0= 0.0428, α_1= 0.0429, and α_2= 0.0428. Table 2.7 indicates that alphas are robust to alternative specifications of the multinomial logit.

There are three reasons that led us to consider estimating the value of K (= y_{i0}/w_i) from the household survey instead of assuming K=1 as in BFL. First, it eliminates arbitrariness in identifying the parameter that measures the ratio of total contribution to household income and market wages for children not enrolled in school. Second, evidence from the survey indicates that K is different from 1. The group of children not attending school can generate domestic production and may receive income other than those from the market (transfers from other households or institutions). If this group was formed only with children working, K = 1 would be a consistent assumption. Empirical evidence indicates that in Mexico (both in 1996 and 2005) only half of those not attending school participate in the labor market. Third, note that by assuming K=1 this could lead to an overestimation of the impact of transfers on the school attendance and on the reduction of child employment due to an overestimation of the alphas. According to the survey data, the school attendance overestimation is 6 percent for children between 12 and 15 years old and 20 percent for kids between 16 and 18 years old.[33]

6. Scenarios and results

The simulations exercises consider changes in the nutrition component of the cash transfer as well as in the educational component. The objective is to focus on the school attendance outcomes that result from changes in the program's rules and in the monetary value of the transfers. Figure 1 illustrates school attendance for poor children by gender during the mid 1990s when the program was implemented. The right vertical axis indicates the amount of the cash transfer for the educational component in 2005.

[33] More details on this are available upon request.

A simple robustness exercise: How good is the empirical model?

The purpose of this exercise is to examine how well the model predicts schooling decisions in 2005. The exercise consists of applying the 2005 program rules to the 1996 survey data with the objective of comparing outcomes of the simulation to the 'actual' household survey data, using the estimated coefficients and the 1996 values of the independent variables. Between 1996 and 2005, in addition to program effects, there were also changes in the demographics and other social economic indicators, and the simulation takes into account such changes. In order to do this, we modify the values of each independent variable in the 1996 survey database considering the changes observed between 1996 and 2005 for 20 population percentiles based on family income per capita (in 1996 prices).[34] Figure 2.2 displays the proportion of 9 to 18 years old that are out of school; this figure only considers poor kids (as defined by the program). The blue line is the observed 1996 values and the dotted blue line displays the 2005 observed values. The simulated model is the green line. School absence for poor children increases with age and school attendance is high for children younger than 12. The model simulates the 2005 scenario fairly well; on average the model replicates the 2005 data in 93.2 percent of the cases.

Scenarios

The baseline scenario consists of applying the 2005 program rules and the estimated parameters of the model to the 1996 data.[35] The schooling decisions are detailed in table 2.8 for different age groups. Comparing the simulated vector of schooling decisions to the original observed vector yields a measure of the program effectiveness. As a result of the program some children moved from occupational choice $S_i=0$ (not attending school) to attending school/working part time

[34] After checking that the model predicts well the situation prevailing in 2005, we simulate the impact due to changes of structure and levels of program's transfers, applying the 2005 program rules and the estimated parameters of the model to the 1996 data.
[35] Additionally, the simulations could be carried out starting from the predicted situation in 2005 as baseline scenario, that is, modifying the values of the transfers and holding the values of other independent variables constant.

(S_i=1) or attending school and not working in the market (S_i=2). Table 2.8 displays the changes in occupational status for different age groups.

The first set of columns of table 2.8 displays results for 12-15 year old group. Before program implementation, around 21 percent of the children were not attending school; about 7.4 percent attended school and worked in the labor market and about 71.6 percent only attended school. Note that when considering poor households, around 33 percent did not attend school, about 11.6 percent attended school and worked in the market and 55.3 percent attended school and did not work in the market. The off-diagonal bold numbers in table 2.8 represent the changes in educational attainment with the 2005 program rules in place. For the age group displayed in the first column (12-15 year old) this represents an increment of about 1.2 percent in school enrolment for all households and 2.7 percent for poor households.

Columns 2 and 3 display the same information for children aged 16-18 and for children aged 12-18. The effects of the program are especially noticeable for the 16-18 year old group. For example, for poor households with children in this age group, there is an increase in school enrolment of around 4.5 percent where only around one percent remains working and studying while around 3.5 percent are studying and not working in the market. Among the 12-18 year olds, the same pattern is observed. There is an increase in school enrolment as a result of the income transfers and this effect is larger for poor households.

Simulation' results

The first scenario considers an increase of 45 pesos (26%) in the nutritional cash transfer while the school allowance remains the same as in 2005. The transfer is conditional on the household being poor (according to the program) and does not require the household to have children. This simulation sheds light on the importance of the conditionality.

The next scenarios propose changes in the design and amount of the cash transfers. Scenario 2 and 3 suspends the benefit for students in grades 3 to 5 of primary school; only those students on grades 6 and above (last year of primary school, secondary and high school students) qualify for the benefits. In Scenario 2 the increase in the allowance is proportional to the money saved by suspending the benefits from grades 3 to 5; under this scenario the program's budget remains the same. Scenario 3 considers tripling the cash transfer allowance to grades 6 and above.

Scenarios 4 and 5 introduce increments in the cash transfers, but without eliminating the transfers to the primary students. Scenario 4 considers a 26% (45 pesos) increase in the nutritional allowance plus a scheme of transfers that increases the school transfer for secondary and high school students. Scenario 4 was simulated gradually, increasing the transfers by 100%, 200% and 300%. The reported results are for the extreme case where the transfers were tripled. Scenario 5 quadruples the benefits for secondary and high school students without an increase in nutritional component. The ceiling in the income transfer amount a household can receive is also dropped.

Scenario 6 considers a new scheme of transfers to secondary and high school students based on the average reported wage of the working children in the 2005 survey. Finally, Scenario 7 considers a reduction in the transfers by half of that in the baseline scenario. Table 2.9 summarizes the simulation results and shows the changes in the occupational status of the children. The reported results are for poor households only.

The simulations indicate that an increase in the nutritional component (scenario 1) did not affect school enrolment when compared to the baseline scenario, indicating that the conditionality is important to promote school enrolment.[36] The elimination of school allowance for grades 3 to 5 indicates that eliminating or reducing school subsidies for primary education and increasing the transfer for older students raises overall school enrolment. In scenario 2 the number of children that do not attend school dropped by 0.8 percent and 0.5 percent for the 12-18 and 9-18 year old groups. In order to examine the elasticity of the demand for school in the context of a CCT, in

[36] This is in line with the Brazilian experience reported in Bourguignon et al. (2003) where they simulate the *Bolsa-Escola* transfer without conditionality.

Scenarios 3 to 5 the amount of transfers is incremented substantially. In Scenario 3 the number of children that do not attend school dropped by five percent for the age group 12-18 and by 3.19 percent for the age group 9-18. Note that under scenario 3 the program budget increases by around 50 percent.

Scenario 4 indicates a substantial increase in school attendance indicating that households respond to the cash incentive. Amongst the selected scenarios, this was the one that showed the best results since 50 percent of the children aged 12-18 are attending school and not working and only 25.7 percent of the children 9-18 are not attending school. The budget of the program increases substantially by 133%. In Scenario 5 for the group aged 12 to 18 years old, school attendance increases by around 4.7 percentage points when compared to the baseline scenario and by around 8 percentage points in relation to the control data before the program implementation.

In Scenario 6, the budget of the program increases by less that 1.5 percent. The simulations indicate that in aggregate terms there are some gains in school enrolment. For the age group 12-18 years old there is a reduction in the "out-of-school" group of around 0.6 percent. Scenario 7 reduces the school subsidy by half and the school attendance decreases by 2.6 percentage points for the group 12-18 year old. Scenario 7 indicates that schooling decisions amongst poor households are sensitive to the transfer amount.

Table 2.10 depicts the results of 5 additional simulation scenarios allowing for an in dept look at the effects of the transfer amount on school enrolment considering the program's current budget in all proposed schemes of transfers. The simulations starts by eliminating transfers for those on grades 3 to 5 and redistributing the savings evenly for those on grades 6-12—scenario (A). Next, in scenario (B) transfers are eliminated from grades 3 to 6 and the savings are distributed evenly for those on grades 7-12. This sequence is carried out until scenario (E) where transfers are given only to those in high-school. We focus on increasing school attendance for poor children aged 12 to 18 years old. For the sub-group of adolescents aged 12 to 15, note that as the transfers are eliminated and given to older students, there is a reduction in school attendance, indicating the importance of the conditionality. Attendance drops significantly under scenarios D and E in which the transfers are handled only to high school students. However, for adolescents aged 16 to 18 years old, note that school attendance increases by 2.5 percentage points under scenario C where the transfer are handled to those on grades 8 and above (i.e. after the second year of secondary school). The last row of table 2.9 averages out the effects of the different schemes for all adolescents. Simulations exercises like this are useful for analyzing the size of the transfer for this kind of program.

Table 2.11 summarizes frequently used poverty and inequality indicators for all the scenarios described in Table 2.9. Comparing the baseline to the 1996 observed indicators, note that the program reduces the incidence of poverty (FGT(0)) by two percentage points at the national level. The reduction is more pronounced in rural areas where poverty incidence is reduced by four percentage points. The Gini coefficient falls from 0.527 to 0.512 indicating little progress in inequality reduction. The mean log deviation which is more sensitive to changes in the bottom of the income distribution changes from 0.487 to 0.449.

Our results are similar to those found for Brazil by BFL. It is noteworthy the similarities in household behavior in Mexico and Brazil. In both CCTs, it appears that the program is effective in increasing school attendance of poor households. In other words, transfers generate significant impacts on school attendance for the group of children that are not attending school and marginal impacts for those who attend school and work. It should be noted, however, that the effect of cash transfers on school attendance is smaller for Mexico's *Oportunidades* than that for Brazil's *Bolsa Familia*. This result might be driven by the fact that school enrollment was about 40 percent lower in Brazil when the program was implemented, even though the socioeconomic profile of children (10 to 15 years old) of both countries is similar. Moreover, the parameter K may be another reason why the impact is greater for Brazil. As previously discussed, we have suggested that assuming K=1 could lead to an overestimation of the transfers' impact on school attendance because the alpha parameters are also overestimated.

Concluding Remarks:

This paper applies the BFL methodology to a Mexican nationally representative household survey data and assesses the effects of changes in the CCT program design by means of micro-simulations. The paper relaxes the BFL model identification assumption, which is shown to lead to an overestimation of the transfers' impact on school attendance. The findings indicate that the modified BFL model is a well-suited framework for simulating the impact of changes in CCT on the incidence of poverty in the short-run through its effect on school attendance. Counterfactual simulations are carried out to explore different combinations of transfers' schemes. One of the counterfactual simulation outcomes shows that eliminating or even reducing school subsidies for primary education and using the savings to increase the transfer for students in advanced grades raises overall school enrolment while keeping the program's budget unchanged.

Using a framework that can be implemented with a household survey we reach similar results to those from Todd and Wolpin (2006) that use a more complex model as well as experimental data. Both papers conclude that to increase school attendance of high-school students requires a much higher transfer and that eliminating subsidies for primary education and using the savings to increase higher grades subsidies can increase school attendance without changing the program's current budget a result that is in line with Attanazio et al. (2001) back-loading proposal i.e. "offering more resources to older children and less to relatively young one". The simulations also show that increasing school attendance for higher grade level students through CCTs can be relatively expensive, suggesting that alternative interventions complementary to the CCTs might be needed to promote school attendance at the high school level. Analyzing the differences between rural and urban poverty incidence and longer term human capital accumulation is a natural extension of this work that can further shed light on CCT program design.

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Table 2.1: Educational Transfers by Grade and Gender (Pesos per Month, 2005)*

Grade / Level	Boys	Girls
Primary School		
Grade 3	115	115
Grade 4	135	135
Grade 5	170	170
Grade 6	230	230
Middle School		
Grade 7	335	355
Grade 8	355	390
Grade 9	370	430
High School		
Grade 10	560	645
Grade 11	605	685
Grade 12	640	730

* The maximum amounts per family were 875 pesos for primary and secondary; 730 pesos for high-school. This does not include the transfers for school supplies described in section 2.

Note: 10 pesos is approximately equal to 1 US dollar, at the 2005 exchange rate

Source: www.oportunidades.gob.mx/informacion_general/main_ma.html

Table 2.2 : Occupational Choice of Children (percentage)

	1996				2005			
Age	Not attending School	Attending school and working	Attending school (only)	Total	Not attending School	Attending school and working	Attending school (only)	Total
7	2.7	0.0	97.3	100.0	1.9	0.0	98.1	100.0
8	2.1	0.0	97.9	100.0	1.7	0.0	98.3	100.0
9	2.6	0.0	97.4	100.0	1.4	0.0	98.6	100.0
10	3.6	0.0	96.4	100.0	2.3	0.0	97.8	100.0
11	3.6	0.0	96.5	100.0	1.6	0.0	98.4	100.0
12	8.9	7.2	83.9	100.0	5.5	6.0	88.5	100.0
13	15.7	8.6	75.7	100.0	8.2	6.4	85.4	100.0
14	24.2	8.3	67.4	100.0	14.1	9.2	76.6	100.0
15	36.2	5.3	58.5	100.0	26.8	8.2	65.0	100.0
16	45.7	7.2	47.2	100.0	34.8	7.9	57.3	100.0
17	56.3	6.7	37.0	100.0	47.5	9.2	43.3	100.0
18	67.2	6.1	26.7	100.0	57.7	7.8	34.5	100.0
Total	21.5	4.0	74.4	100.0	16.9	4.6	78.5	100.0

Source: Author's calculation based on the ENIGH 1996 and ENIGH 2005

Table 2.3: Sample means. Characteristics of children and their households (ages 12-18)

Characteristics	1996 Not attending School	1996 Attending School and Working	1996 Attending School (only)	1996 Total	2005 Not attending School	2005 Attending School and Working	2005 Attending School (only)	2005 Total
Age	16.0	14.8	14.3	14.9	16.3	15.1	14.3	14.9
Years of education	6.0	7.4	7.6	7.0	7.3	8.2	7.8	7.7
Household income *	2841	2595	4078	3533	3343	3847	4630	4219
Wage income 12-18 years old*	199	146	1	82	328	252	4	111
Years of educ. Household head	3.7	4.5	6.5	5.3	4.9	6.3	7.7	6.8
Years of educ. Spouse	2.7	3.2	4.9	4.0	3.4	4.2	5.7	5.0
Age household head	45.4	45.2	44.8	45.1	45.2	45.0	45.4	45.3
Age spouse	33.7	34.2	34.1	34.0	31.0	30.8	32.7	32.1
Men head of the household	0.48	0.66	0.50	0.51	0.49	0.64	0.50	0.51
Rural (housing)	0.57	0.57	0.33	0.44	0.50	0.48	0.37	0.41
Lives in Northeast area	0.12	0.06	0.13	0.12	0.12	0.06	0.14	0.13
Lives in Northwest area	0.06	0.05	0.08	0.07	0.07	0.10	0.08	0.08
Lives in Center-West area	0.28	0.25	0.20	0.23	0.28	0.30	0.21	0.24
Lives in Center area	0.29	0.31	0.38	0.34	0.28	0.20	0.33	0.31
Lives in South-Southeast area	0.25	0.33	0.21	0.23	0.25	0.33	0.24	0.25
Num. of members age 0-5	0.62	0.50	0.40	0.48	0.48	0.34	0.27	0.33
Regis. students x teacher (Primary)	28.1	28.2	27.8	28.0	26.3	25.9	26.2	26.2
Regis. students x school (Primary)	161.9	158.9	175.4	169.4	163.0	151.9	172.8	168.5
Regis. students x teacher (Secondary)	18.1	18.4	17.6	17.8	17.7	17.3	17.5	17.5
Regis. students x school (Secondary)	202.6	191.0	224.0	214.0	199.5	190.2	209.6	205.3
Distance to school Primary**	2.0	1.9	2.2	2.1	2.0	1.9	2.1	2.1
Distance to school Secondary**	22.5	18.5	25.2	23.7	15.7	13.7	16.0	15.7
Distance to school High-School**	37.1	34.1	35.0	35.7	29.5	27.6	28.8	28.9

* All figures per month in 1996 prices: IPC96 = 51.512, IPC05 = 114.027. ** distance (Km) to the closest school

Source: Author's calculation based on ENIGH de 1996 and 2005

Table 2.4: School enrollment and occupation of children by age groups and socio-economic status (1996 and 2005)

Age (years)	1996 Not attending School	1996 Attending School and Working	1996 Attending School (only)	1996 Total	2005 Not attending School	2005 Attending School and Working	2005 Attending School (only)	2005 Total
All children								
9-11	3.27	0.00	96.73	100	1.75	0.00	98.25	100
12-15	21.01	7.36	71.63	100	13.43	7.42	79.15	100
16-18	56.21	6.69	37.10	100	46.83	8.33	44.84	100
9-18	25.55	4.89	69.56	100	19.64	5.49	74.87	100
Poor children								
9-11	5.42	0.00	94.58	100	3.68	0.00	96.32	100
12-15	33.08	11.57	55.35	100	22.86	10.34	66.80	100
16-18	79.05	6.10	14.86	100	67.82	6.85	25.33	100
9-18	32.9	6.03	61.07	100	26.09	5.85	68.06	100

Source: Author's calculation based on ENIGH1996 and ENIGH2005

Table 2.5: Log Earnings Regression 12-18 year-old children reporting earnings

	Coef.	t	P>t
Works and studies	-0.4183	-5.93	0.0000
Age	0.1438	6.86	0.0000
Years of education	0.0196	1.81	0.0700
Dummy for Male	0.1364	2.87	0.0040
Log of median wage (12-18 years old)	0.8502	17.83	0.0000
School-age gap	0.0142	1.77	0.0780
Dummy for rural areas	-0.0079	-0.16	0.8760
Constant	-1.9222	-4.75	0.0000
No Observations	1810		
R- squared	0.3025		

Source: Author's calculation based on the 1996 ENIGH

Table 2.6: Occupational Structure Multinomial Logit Model
Marginal Effects and P-Values (Working and not attending school is the reference group)

	Working and Studying		Studying (only)	
	dy/dx	P>z	dy/dx	P>z
Total household income	0.0000	0.0370	0.0000	0.1080
Children's earnings (predicted)	-0.0006	0.0000	0.0005	0.0000
Number of members	-0.0004	0.6460	-0.0002	0.9610
Age	0.0101	0.0000	-0.2335	0.0000
Years of education	0.0093	0.0000	0.1102	0.0000
School-age gap	0.0026	0.0000	-0.0099	0.0000
Dummy for Male	0.0382	0.0000	0.0055	0.6770
Years of education head	-0.0008	0.0790	0.0168	0.0000
Years of education spouse head	-0.0008	0.1190	0.0092	0.0010
Age household head	-0.0003	0.0430	0.0036	0.0000
Age spouse head	-0.0001	0.3010	-0.0003	0.5530
Number of members age 0-5	0.0019	0.3680	-0.0319	0.0030
Rural*	-0.0150	0.0000	-0.1377	0.0000
Northeast*	-0.0063	0.2760	-0.0132	0.6340
West (Central)*	0.0439	0.0250	0.0776	0.0140
Central*	-0.0206	0.0000	0.1162	0.0000
South* -	-0.0219	0.0000	0.1995	0.0000
Rank of child (oldest -youngest)	0.0005	0.7580	-0.0157	0.0590
Average distance- primary school**	0.0000	0.5120	0.0000	0.8730
Average distance- secondary school**	0.0000	0.0180	0.0000	0.7430
Average distance high-school**	0.0000	0.0020	0.0000	0.1680
Regis. students x teacher (Primary)	0.0022	0.0000	0.0005	0.8790
Regis. students x teacher (Secondary)	0.0028	0.0000	-0.0088	0.0120
Regis. students x teacher (High-school)	-0.0040	0.0000	-0.0001	0.9740

Note: (*) dy/dx is for discrete change of dummy variable from 0 to 1
(**) distance (Km) to the closest school
Pseudo R^2 = 0.3651: number of observations = 10696
Source: Author's calculation based on the 1996 ENIGH

Table 2.7: Summary of alphas (robustness)

Multinomial logit	α_0	α_1	α_2
With parents' education linearly	0.04282	0.04286	0.04286
With parents' education dummies*	0.04277	0.04281	0.04281

* Differences are not significant according the 95% confidence interval of estimated parameter used to generate the alphas, Coefficients of this multinomial logit are in the Appendix.
Source: Author's calculation based on the 1996 ENIGH

Table 2.8: Simulated effect of *Progresa-Oportunidades* on school attendance and work status (all children 12-18 years old)

	12-15 years old				16-18 years old				12-18 years old			
	Not attends School	Attends School and Works	Attends School (only)	Total	Not attends School	Attends School and Works	Attends School (only)	Total	Not attends School	Attends School and Works	Attends School (only)	Total
All children												
Does not attend school	19.8	0.0	**1.2**	21.0	54.7	**0.3**	**1.2**	56.2	34.3	**0.1**	**1.2**	35.6
Attends School and Works	0.0	7.4	0.0	7.4	0.0	6.7	0.0	6.7	0.0	7.1	0.0	7.1
Attends School	0.0	0.0	71.6	71.6	0.0	0.0	37.1	37.1	0.0	0.0	57.3	57.3
Total	19.8	7.4	72.8	100.0	54.7	7.0	38.3	100.0	34.3	7.2	58.5	100.0
Poor children												
Out of School	30.3	0.0	**2.7**	33.1	74.5	**1.0**	**3.5**	79.1	46.0	**0.4**	**3.0**	49.3
Attends School and Works	0.0	11.6	0.0	11.6	0.0	6.1	0.0	6.1	0.0	9.6	0.0	9.6
Attends School	0.0	0.0	55.4	55.4	0.0	0.0	14.9	14.9	0.0	0.0	41.0	41.0
Total	30.3	11.6	58.1	100.0	74.5	7.1	18.4	100.0	46.0	10.0	44.0	100.0

Source: Author's calculation based on the ENIGH 1996

Table 2.9: Simulations - Summary of Results and Selected Scenarios - Poor Children only

	Baseline	Scenarios						
		1	2	3	4	5	6	7
Age 12-18								
Not attending school	46.0	46.0	45.2	40.9	38.4	41.3	45.4	48.5
Attending school and working	10.0	10.0	10.2	10.9	11.3	10.9	10.1	9.7
Going to school and not working	44.0	44.0	44.7	48.2	50.4	47.9	44.5	41.8
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Age 9 - 18								
Not attending school	30.6	30.6	30.1	27.4	25.8	27.6	30.3	32.4
Attending school and working	6.3	6.3	6.4	6.8	7.0	6.8	6.4	6.1
Going to school and not working	63.2	63.2	63.5	65.8	67.2	65.6	63.4	61.6
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Program's Budget *	100.0	111.1	100.0	156.1	233.2	195.9	101.5	72.4

* percentage of current expenditures
Scenarios: Baseline-- Transfers as in 2005
1- Increase in nutritional component (45 pesos= 26%). No change in school subsidies
2-Suspension of school transfers 3-5 primary and redistribute equally to all grades. Same nutritional component.
3-Suspension of school transfers 3-5 primary and multiply transfers by 3.Same nutritional component
4- Increase in nutritional component (45 pesos= 26%) and 300% increase on school transfer after year 6.
5-Quadruple transfers after year 6 without a ceiling. Same nutritional component.
6-Set school transfers equal to 2005 average wage by age. Same nutritional component
7- Cut current school subsidies in half
Source: Author's calculations

Table 2.10: Simulations – Same budget
Summary of Results and Selected Scenarios (Poor children only)

	Baseline	Scenarios (all with the same budget)*				
		A	B	C	D	E
Age 12-15						
Does not attend school	30.3	29.7	30.3	30.5	31.4	32.6
Attends school	69.7	70.3	69.7	69.5	68.6	67.4
Attends School and Works	11.6	11.6	11.7	11.7	11.6	11.6
Attends School (only)	58.1	58.7	58.0	57.9	57.0	55.8
Total	100.0	100.0	100.0	100.0	100.0	100.0
Age 16-18						
Does not attend school	74.5	73.4	72.1	72.0	72.5	76.5
Attends school	25.5	26.6	27.9	28.0	27.5	23.5
Attends School and Works	7.1	7.5	7.7	7.9	8.3	6.8
Attends School (only)	18.4	19.1	20.2	20.1	19.2	16.7
Total	100.0	100.0	100.0	100.0	100.0	100.0
Age 12-18						
Does not attend school	46.0	45.2	45.1	45.2	45.9	48.1
Attends school	54.0	54.8	54.9	54.8	54.1	51.9
Attends School and Works	10.0	10.2	10.3	10.3	10.4	9.9
Attends School (only)	44.0	44.7	44.7	44.5	43.7	42.0
Total	100.0	100.0	100.0	100.0	100.0	100.0

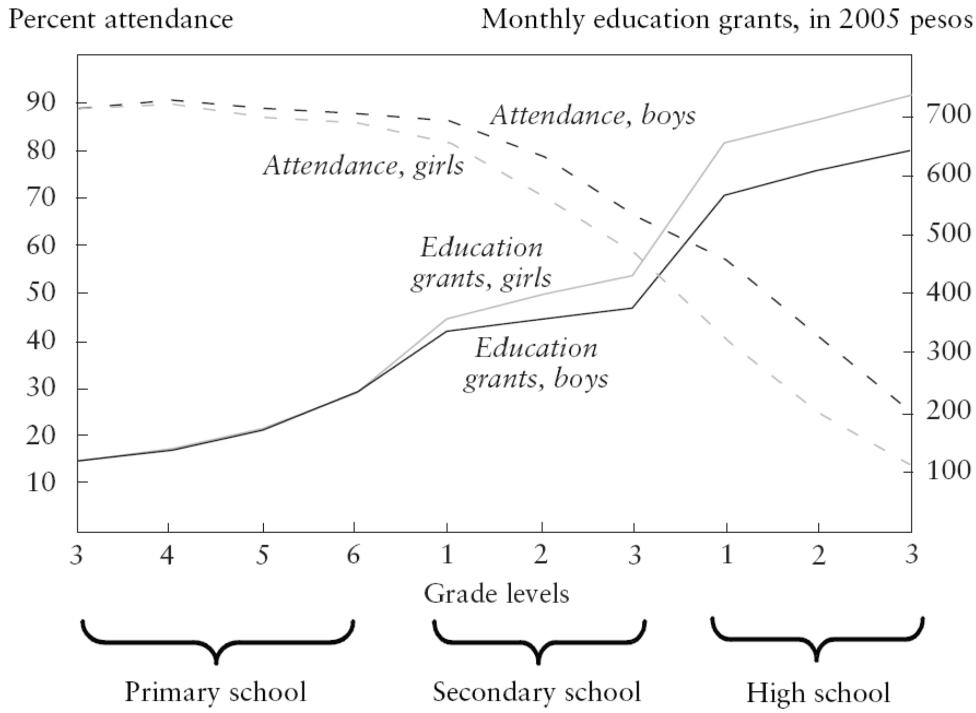
Scenarios:
(A) Suspension of school transfers 3-5 grades and redistribute equally to all other grades
(B) Suspension of school transfers 3-6 grades and redistribute equally to all other grades
(C) Suspension of school transfers 3-7 grades and redistribute equally to all other grades
(D) Suspension of school transfers 3-8 grades and redistribute equally to all other grades
(E) Suspension of school transfers 3-9 grades and redistribute equally to all other grades
* Program budget as in 2005- same nutritional transfer.

Table 2.11: Effects on Poverty and Inequality Indicators

	Area	Poverty indicators			Inequality Indicators		
		FGT_0	FGT_1	FGT_2	Gini coefficient	Theil Index	Mean Log Deviation
Observed 1996	Urban	0.361	0.127	0.060	0.503	0.516	0.433
	Rural	0.605	0.254	0.139	0.441	0.368	0.330
	All	0.461	0.179	0.092	0.527	0.570	0.487
Baseline	Urban	0.355	0.117	0.052	0.497	0.507	0.418
	Rural	0.561	0.209	0.103	0.412	0.324	0.283
	All	0.439	0.155	0.073	0.512	0.544	0.450
Scenario 1	Urban	0.354	0.116	0.051	0.496	0.506	0.416
	Rural	0.553	0.204	0.100	0.409	0.320	0.279
	All	0.436	0.152	0.071	0.511	0.541	0.446
Scenario 2	Urban	0.354	0.117	0.052	0.497	0.507	0.418
	Rural	0.556	0.211	0.107	0.414	0.327	0.289
	All	0.436	0.156	0.075	0.513	0.545	0.452
Scenario 3	Urban	0.348	0.112	0.050	0.494	0.502	0.412
	Rural	0.531	0.195	0.097	0.406	0.313	0.278
	All	0.423	0.146	0.069	0.506	0.533	0.440
Scenario 4	Urban	0.343	0.107	0.046	0.490	0.496	0.404
	Rural	0.493	0.173	0.082	0.393	0.293	0.260
	All	0.404	0.134	0.061	0.497	0.518	0.422
Scenario 5	Urban	0.344	0.110	0.048	0.492	0.499	0.408
	Rural	0.515	0.187	0.092	0.403	0.306	0.273
	All	0.414	0.141	0.066	0.503	0.526	0.433
Scenario 6	Urban	0.353	0.117	0.053	0.497	0.507	0.419
	Rural	0.553	0.214	0.109	0.417	0.330	0.294
	All	0.435	0.157	0.076	0.513	0.545	0.455
Scenario 7	Urban	0.358	0.120	0.054	0.498	0.509	0.422
	Rural	0.573	0.221	0.112	0.419	0.335	0.295
	All	0.446	0.161	0.078	0.516	0.551	0.459

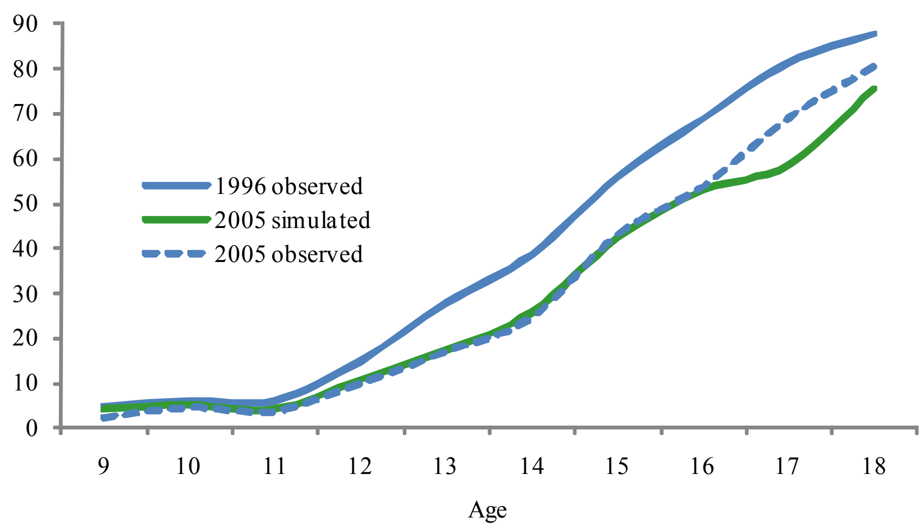
Source: Author's calculations
Baseline-- Transfers as in 2005
1- Increase in nutritional component (45 pesos= 26%). No change in school subsidies.
2-Suspension of school transfers 3-5 primary and redistribute equally to all grades. Same nutritional component.
3-Suspension of school transfers 3-5 primary and multiply transfers by 3.Same nutritional component.
4- Increase in nutritional component (45 pesos= 26%) and 300% increase on school transfer after year 6.
5-Quadruple transfers after year 6 without a ceiling. Same nutritional component.
6-Set school transfers equal to 2005 average wage by age. Same nutritional component....
7- Cut current school subsidies in half.

Figure 2.1: School attendance and education grants



Source: Levy (2006)

Figure 2.2: Observed and simulated not attendance school (poor children)



Source: Author's calculation based on the ENIGH 1996 and 2005

Chapter Three
Spatial Poverty Traps? An Empirical Investigation of Consumption Growth, Geographical Variables, and Infrastructure Using Micro Data for Ecuador

1. Introduction

Poverty reduction has been a policy priority in most developing countries. The United Nation's Millennium Development Goals[37] (MDGs) have set the broad contours of the agenda for economic development in emerging and poor countries. The first goal is to reduce poverty by half by 2015. When analyzing data beyond national averages, there is widespread evidence showing persistence of poverty incidence in specific areas. This holds even when the country in question has experienced sustained periods of rapid economic growth. Several factors might account for the persistence of poverty, reinforcing the existence of spatial poverty "traps", including geographic conditions. As defined by Azariadis and Stachurski (2005), a poverty trap is any reinforcing mechanism that causes poverty to persist. This indicates that there might be thresholds in some productive assets, and if the individual is below this cut off, then recovery becomes impossible, and one is trapped in an equilibrium level of very low asset holdings and poverty. Some examples of market failures that are likely to contribute to poverty traps are credit markets failures, geographic and other externalities, and risk induced traps (Dercon, 2003). This paper focus on the existence of spatial poverty traps.[38]

To better understand the occurrence of spatial poverty traps, one needs to consider its occurrence along with households' decisions, such as the choice to live in a poor neighborhood. Assuming perfect household spatial mobility (e.g., no costs of moving between, within or across regions and no zoning laws that keep poor people out of richer neighborhoods), one expects that households living in poor areas would over time move to more productive (less poor) areas where income per capita is higher. The occurrence of spatial poverty traps implies the existence

[37] The Millennium Development Goals (MDGs) are eight goals to be achieved by 2015 that respond to the world's main development challenges. The MDGs are drawn from the actions and targets contained in the Millennium Declaration that was adopted by 189 nations-and signed by 147 heads of state and governments during the United Nations Millennium Summit in September 2000.
[38] We use the terms geographical poverty traps and spatial poverty traps interchangeably.

of economically significant relocation costs (as the relative costs of moving can be extremely high for poorer households) or informational asymmetries that prevent households from moving from poor areas to higher income areas. High housing costs and costs of searching for a well-paying job might have hindered relocation in many developing countries, but in light of massive rural-urban migration that occurred in every major developed and developing country, such costs are unlikely to be the main cause of poverty traps. In addition, households that move to higher-income areas also face high relative prices for transportation, housing, and food. Cultural barriers such as language and regional traditions (which provide risk sharing and social protection networks within poorer communities) may also deter poor households from moving.

Ravalion (1998) highlights two hypotheses that shed light on the reasons behind why some areas remain poor even after periods of rapid national growth. One view is that households are free (in an economic sense) to move between regions, but spatial concentrations of individuals occur because people with similar characteristics tend to concentrate. In this case, poverty traps occur because of the constant concentration of people with personal attributes that inhibit growth in their living standards. According to this view, otherwise identical individuals will have the same growth prospects independently of where they live; thus, there is no clear role to spatial characteristics or geography and the location of residence does not really matter for consumption growth. Alternatively, spatial characteristics may have a causal role in determining how households' welfare changes over time depending on where they reside. Spatial poverty traps could occur because of pure geographic factors, such as climate conditions and the spatial provision of public goods. According to the spatial (geographic) poverty trap view, spatial mobility is relatively limited and households that live in well-endowed areas have a higher probability of escaping poverty when compared to similar households that live in poor areas.

Poverty traps may be due in part to insufficient local supply of public goods and infrastructure as well as other geographic factors. In this case, two individuals with the same characteristics do not experience the same improvements on living standards if they live in areas with different endowments of geographic capital. This could occur in a simple growth model augmented with geographic capital (Jalan and Ravalion, 2002) which assumes that the marginal return to a given level of schooling or capital depends on the spatial location.

This paper analyzes the role of geography and the spatial distribution of infrastructure in explaining the persistence of poverty in Ecuador. Specifically, this paper examines the relationship between household consumption growth and spatial variables by using a test for the presence of spatial or geographic poverty traps. We use a rich data set that includes a range of variables: (i) pure geographic characteristics such as climate conditions; (ii) the spatial provision of infrastructure; and (iii) demographic and socio-economic variables. The findings indicate a significant impact of the spatial distribution of geographic factors on income, which in part, explains the existence of spatial poverty traps in Ecuador; these are consistent with the evidence of Jalan and Ravallion (2002) report on China. The findings are in line with Ecuador's geographic diversity, including the unequal spatial distribution of geographic capital at the sub-national level.

The paper is organized as follows. The next section reviews the relationship and evidence between spatial and geographic variables and household measures of wellbeing in Latin America, with a focus on Ecuador.[39] Section 3 motivates and describes the empirical methodology. Section 4 summarizes the empirical results and Section 5 concludes.

2. Poverty Traps, Development and Geography

This section starts by discussing the macroeconomics literature on income convergence and poverty traps followed by a review of Latin America's country case studies that focus on the importance of geographic aspects on economic development.[40] Latin America has large concentrations of people in areas that are geographically challenging to inhabit. This owes to geography as much as to the lack of adequate provision of public infrastructure. In general,

[39] We use the general term "well being" given that the papers mentioned in the next section covers a variety of topics, including health indicators and household consumption.

40 Many of the papers discussed here are also summarized in Gallup, Gaviria, and Lora (2003); the authors did not include Ecuador in their analysis.

regions with low levels of geographic capital (e.g., inadequate provision of infrastructure) have had higher levels of poverty, worse health conditions, lower educational achievements, and limited access to basic services (Gallup et al, 2003). A specific example is the case of Peru. Escobal and Torero (2000) report that in Peru a heavy concentration of poor people lives in the most geographically-adverse zones such as the provinces in the highlands and in the Amazon rainforest (selva region).

Standard growth models shed light on the reasons why income differences across countries arise. However, these models are usually tested using country-level data and significant differences between growth at the national level and at the household level tend to persist over time. At the country level, the neoclassical growth theory assumes diminishing returns to capital (and other factors of production) and conjectures that poor nations will tend to catch up over time with the incomes of richer nations— the convergence hypothesis.[41] Empirical evidence in favor of convergence is mixed and two alternative arguments have emerged to justify the divergence observed in the data.

In the economic growth literature the term "convergence" is frequently used in two different contexts. First, the “club convergence” approach indicates that distinct groups of countries will converge to different equilibria depending on their initial conditions (Baumol, 1986); under this model countries converge in clubs. Note however that even if there is convergence within clubs, this does not imply convergence across clubs. From this perspective, after controlling for a set of country-specific characteristics, high- and low-income equilibria are possible. The multiple equilibria growth models argue that there is the possibility of poverty traps related to thresholds where returns are locally increasing (Azariades and Drazen, 1990). When returns are locally increasing, the relationship between wealth (assets) and its marginal return is positive. These models emphasize the need for a big push to cross the threshold and move from the low equilibrium to the higher one(s) (where locally increasing returns to scale are available).

[41] The empirical evidence does not fully support the convergence argument. We will not get into this discussion for a contrary view of the convergence theory see Lant Pritchett (1997).

The focus on externalities, such as geographic variables, leads to the possibility of divergent growth paths. At the individual level, there are individual characteristics and other reasons that generate multiple equilibria and inhibit initially poor households to draw near their wealthier neighbors. This might be linked to individual characteristics and intra-household decisions that affect the level of well-being. As noted by Carter and Barrett (2006), the empirical literature on poverty traps using micro data is relatively small and generally uses parametric methods to explore the dynamics of household income or consumption.

Geography can also have a causal role in poverty dynamics. If geographic externalities change returns to private investment, affect borrowing constraints and hinder capital mobility, then poor areas can be "trapped" in a vicious poverty cycle. This can be true even assuming diminishing returns to investment, as poor areas experience low growth rates (Jalan and Ravallion, 2002). The geography of poverty takes into account distinct dimensions of geographic aspects such as land productivity, climate, population settlement, infrastructure, and investment in specific areas. The famous example of the relationship between geography and economic development (Gallup, Sachs and Mellinger, 1999) analyzes the association between GDP per capita and latitude. The results indicate that countries that are close to the tropics are poorer when compared to the ones that have higher latitudes. Gallup et al. (1999) also found that countries that are in the coastal areas are richer (have a higher GDP per capita) than those that do not have access to the sea (see Figure 3.1). A common criticism of this work claims that the relationship between geography and poverty is not causal and might reflect different colonization patterns and cultural differences. The more recent evidence of the micro data studies at the country level are less subject to such observations because the colonization patterns, cultural differences, and formal institutions are more homogeneous within a country than across countries and regions of the world.

Microeconomic Studies of Geography and Economic Development

The microeconomic studies of geography and economic development allow for a more detailed examination of the relationship between geography and development. These studies use disaggregated data either by the political subdivisions of states and provinces or by geographic regions. Ravallion (2005) uses micro data for rural China and finds evidence of spillovers and other externalities that could form geographical poverty traps. Jalan and Ravallion (2002) consider a panel of households in rural China and investigate the existence of spatial or geographic poverty traps. The main focus of their paper is to determine the impact of geographic variables on household consumption growth. The authors find that consumption growth increases with the local availability of geographic capital such as the availability of roads and the local level of literacy. Jalan and Ravallion (2002) also show empirically that geographic factors affect the returns to capital faced by households. Their results suggest that the factors captured in the geographic variables can be a constraint to household consumption growth.

A different type of micro econometric evidence can be found in Lokshin and Ravallion (2004). They estimate a non-linear dynamic model of household income in two transition economies (Hungary and Russia). The authors calibrate their dynamic model of incomes allowing current income to be a nonlinear function of past income considering attrition from the survey. The main findings are that adjustment to income shocks is nonlinear, and that there is no evidence of non-convexities that would cause temporary adverse shocks to permanently lower household income, (households eventually recover from income shocks) as would be the case in a variety of models of poverty traps. Ravallion and Wodon (1997) use household survey data for Bangladesh and find significant evidence that geography affects living standards. The authors point out that there are sizeable geographic differences in the returns of given households characteristics even after controlling for non-geographic characteristics of the household. They indicate that the results are robust and consistent with the country's migration pattern.

Evidence from Latin America[42]

Esquivel (2000) analyzes the effects of geographic factors on the economic development of Mexico. He notes that geographic variables can explain two thirds of the inter-state variation in income per capita in Mexico. He also finds that the drier Northern states are much richer than the

[42] This section draws from the background papers prepared for the book by Gallup et al (2003) and the book itself. Ecuador is not considered in the analysis.

southern tropical ones and that economic activity is light along the coast and intense in the center of the country. Additionally, there is a strong association between vegetation and economic growth; states in which the vegetation is composed of agricultural areas and woodland tend to grow at lower rates than the other states. Esquivel (2000) analyses the geographic distribution of two indicators: life expectancy and schooling. His results indicate that geographical factors are amongst the main contributors to regional inequalities in Mexico and affect the distribution of life expectancy and schooling. Blum and Cayeros (2002), focus on how Mexico's geographical impact on growth is reinforced by political decisions and their relationship with income, growth and poverty. They argue that the main channel through which geography affects development is though the provision of public goods. For example, they describe the positive effects of public goods provision on higher rates of urbanization and literacy rates. Blum and Cayeros (2002) also point out that the fragmentation of political jurisdiction in the form of municipal governments' proxies for political barriers to mobility and that the lack of household geographical mobility also helps explain the interaction between geography and development.

The empirical evidence for Bolivia also corroborates the strong influence of geography on development. Urquiola et al. (1999) carry out the analysis considering three geographic regions: the Andean, Sub-Andean or Valley, and Lowland regions. The authors do not use the political divisions of states and municipalities as in most studies of this type. A consistent result of their estimations indicates that tropical areas have higher income levels, in contrast with other international cross-country evidence, and reinforces the importance of considering individual country analysis. The relationship between geography and well-being (measured by GDP per capita and social development indices) indicates that the living conditions are better in low altitude cities.

Bitran et al. (2000) studies the relationship between health indicators and geographic factors such as rain and temperature in Peru. The evidence at the province level indicates that geographic factors significantly explain infant mortality and child malnutrition rates. Bitran et al. (2000) also analyzes the effect of natural geography on the effectiveness of government health investments. The authors simulate how public resources devoted to new facilities and doctors could be allocated among the provinces to reduce regional inequality in health status. Finally, Bitran et al. (2000) find that natural geographic factors exacerbate inequality in health, as do existing regional differences in the availability of public services.

Escobal and Torero (2000) also focus on Peru and find that significant differences in household consumption can be explained by spatially uneven provision of public infrastructure. According to the authors, geographic factors are important and indicate that the availability of infrastructure could be limited by the geographic factors and therefore the more adverse geographic regions are the ones with less access to public infrastructure. They point out that policy programs that use regional targeting (i.e. that prioritize intervention in one geographical area over another) are worth even if geographical factors do not significantly explain the bulk of the difference in regional growth these are justified mainly by inequalities in geographical areas. Escobal and Torero (2000) show evidence of large welfare disparities across Peru and reports that a heavy concentration of poor people lives in the most geographically-adverse areas such as the provinces in the highlands and the forest (*selva* region).

In the case of Colombia, Sanchez and Nuñez (2000) show that geographic variables explain between one-third and one-half of household per capita income and its growth rate. The authors also find that there is substantial heterogeneity in the effect of geography on variations in household income. They note that in poor municipalities the effects of geography explain substantially more of the variation, accounting for 25-32 percent of the variation in income per capita and between 24-27 percent of the variation in income per capita growth; however, in rich municipalities geography plays a less significant role, explaining 18-25 percent of the variation in income per capita and 16-17 percent variation in income per capita growth. Amongst the geographic variables the distance to an urban center and the quality of the soil are the variables that contribute the most to changes in income per capita. Furthermore, Sanchez and Nuñez (2000) indicate that altitude, soil quality, and precipitation are the main geographical variables that contribute to population density in Colombia.

Rosenberg et al. (2000) look at the relationship between health and climate change in Brazil. The study uses a cross-section of Brazilian municipalities to estimate the impact of increases in temperature and rainfall and the indirect effects of other geographical factors such as altitude and distance from the ocean on respiratory, water-borne, and vector-transmitted diseases (such as Malaria). The diseases considered account for a sizable proportion of all hospitalizations and deaths in Brazil and are known to be sensitive to climate conditions. Azzoni et al. (1999) explores the role of geographic variables in explaining differences in per capita income between Brazilian states using micro data. They take into account geographical variables such as climate and data on infrastructure, health, and education by birth cohort level. The authors conclude that geographical variables are an important determinant of income growth and explain a great deal of the state fixed effects that reflects structural differences between the states of Brazil.

Ecuador: Economic Background and Geographical Characteristics

After the 2001 crisis when per capita income fell by almost eight percent as a result of unfavorable external conditions and environmental shocks, Ecuador experienced a period of economic recovery. As in previous growth spurts, the growth experienced in the last few years has not benefited all the population equally. Micro-level estimations of poverty and inequality based on the seminal work of Elbers, Lanjouw, and Lanjouw (2002),[43] carried out by international development agencies as well as by the Ecuadorian national statistic offices indicate poverty fell only in a few areas. Poverty rates declined in Ecuador's main cities of Quito and Guayaquil while other regions remained unaffected with poverty rates that were equal or higher than those observed in 1999 (Robles and Luengas, 2007). The evidence available from household surveys, disaggregated by geographic areas, indicates that rural areas benefited least from economic growth.

Ecuador has a diverse natural topography, which in turn is associated with a diverse set of other geographic factors. The country has three main geographic regions, plus an insular region

[43] Elbers, Chris, Jean O. Lanjouw and Peter Lanjouw (2002). "Micro-Level Estimation of Poverty and Inequality." *Econometrica* 71:1, pages 355-364

bordering the Pacific Ocean. The coast comprises the low-lying land in the western part of the country, including the Pacific coastline; the highlands (*la Sierra*) is the high-altitude belt running north to south along the center of the country, its mountainous terrain dominated by the Andes mountain range; and the east (*El Oriente*) comprises the Amazon rainforest areas in the eastern part of the country, accounting for just under half of the country's total surface area, though populated by under five percent of the population. The insular region in the Pacific Ocean comprises the Galapagos Islands, some 1,000 kilometers (620 mi) west of the mainland.

Ecuador ranks first amongst the Latin American countries in the index of Geographical Fragmentation reinforcing the need to consider its geographic diversity. The index of Geographical Fragmentation is defined as the probability that two individuals taken at random from the population live in similar eco-zones (Gallup, Gaviria and Lora, 2003). The index goes from zero, where all the population is settled to the same eco-zone to the hypothetical case where each individual comes from different eco-zones (index equals 1).

While Ecuador is not a particularly large country, it has a great climate variety, mainly determined by its topography. The Pacific coastal area has a tropical climate, with a high precipitation season. The climate in the Andean highlands is temperate and relatively dry. The Amazon basin on the eastern side of the mountains shares the climate of other rain forest zones. Ecuador's main cities are located in geographically different regions; the capital Quito is in the Highlands while the country's largest city, Guayaquil, is on the Coast.

The maps in Figure 3.3 display the heterogeneity within the country for average consumption level (map 1) and some geographical variables (maps 2-4). Darker colors on the consumption map indicates lower levels of consumption, meanwhile darker colors in the geographic variables map indicates adverse geographic conditions. These illustrations are corroborated by the correlation coefficient between geographical variables and consumption as indicated below. When considering population weights, note that all variables are significantly correlated with consumption.

3. Methodology

A Canonical Growth Model

The empirical model presented in this chapter is based on the neoclassical growth model augmented by geographic characteristics. The main objective is to account for the geographic factors that affect the income dynamics of the representative household (*h*). In the model, the potential income of the representative household (*Y*) in period *t* is generated by a production function that has as arguments the level of physical and human capital[44] (*K*) and a set of geographic or spatial factors (G) that can affect the marginal productivity of capital. The production function is given by:

$$Y_{ht} = F(K_{ht}, G_{ht}) \tag{3.1}$$

where *Y* is income, *K* is augmented capital and *G* are the geographical or spatial factors. The production function assumes constant returns to scale in both arguments; according to Euler's theorem it can be written as:

$$F(K_{ht}, G_{ht}) = F_k(K_{ht}, G_{ht})K + F_G(K_{ht}, G_{ht})G \tag{3.2}$$

Furthermore, we assume that the production function assumes positive but diminishing marginal products:

$$F_i(K_{ht}, G_{ht}) > 0 \text{ and } F_{ii}(K_{ht}, G_{ht}) < 0 \text{ for } \quad i = K, G$$

The household maximizes his/her inter-temporal utility function subject to a budget constraint. In what follows, a lower case letter indicates household variables (such as income) while upper case

[44] K is the level of "augmented capital" as it includes physical as well as human capital, a departure from Jalan and Ravallion (2002). For the case of wage-earner households, their augmented capital is reduced to its human component.

letters indicate economy wide or aggregate quantities. For example, y_{ht} is the potential income of household *h* at time *t* and assuming that household h finances its consumption entirely by using all its human and physical capital to generate income given the geographic and spatial characteristics in the model.

The household maximizes its inter-temporal utility

$$\underset{\{c_{h,t}\}}{Max}\sum_{t=0}^{\infty}\beta^{t}U(c_{ht}) \qquad \text{subject to } y_{ht} = F(K_{ht}, G_{ht}) \text{ for all } \quad t \geq 0 \tag{3.3}$$

where $\beta \in (0,1)$ and c_{ht} is household consumption. The constant relative risk aversion (CRRA) utility function is given by:

$$u_{h,t}(c_{h,t}) = \frac{(c_{h,t})^{1-\sigma}}{1-\sigma} \quad \text{we assume } \sigma \to 1 \text{ and it follows that } u_c = \log c$$

Furthermore, assume that there are constraints on access to credit, a reasonable assumption especially for poor households in Latin America, implying that capital is not perfectly mobile across households.[45] The household finances its consumption and investment in physical and human capital entirely from the production function as described below:

$$K_{h,t+1} = (1-\delta)K_{h,t} + F(K_{h,t}, G_{h,t}) - C_{h,t} \qquad \text{for all } t \geq 0 \tag{3.4}$$

where δ is the depreciation rate of augmented capital (0 < δ < 1).

Solving the household maximization problem yields the standard Euler equation:

$$u_{C_t} = \beta u_{C_{t+1}}\left[(1-\delta) + F_K(K_{t+1}, G_{t+1})\right]$$

[45] As in other developing countries, borrowing constraints are common and financial markets are poorly developed. Poor household are even more credit constrained as lenders usually require collateral from their borrowers (Azariades and Stachurski, 2004, Chapter of the Handbook of Economic Growth)

where F_K is the marginal productivity of capital. Increases in the marginal productivity of capital induce increases in consumption if the marginal utility of consumption is decreasing. In this otherwise standard model, geographic and spatial characteristics can influence consumption through their direct effect on the marginal productivity of the household's capital.

After substituting the marginal utilities in the first order conditions, linearizing, and writing the marginal productivity of augmented capital in reduced form one obtains the following equation:

$$\Delta \ln c_{h,t} = \ln c_{h,t} - \ln c_{h,t-1} = \alpha + \beta x'_{h,t} + \gamma z'_h \tag{3.5}$$

where x_{ht} and z_h are vectors of variables containing information on the specific household community (both time-dependent and independent) that affect the marginal productivity of capital.

We assume that in equilibrium the net marginal product of household capital is equalized across households (at a common interest rate). Under the standard assumptions of this class of growth models, this implies that differences in endowments of geographical capital do not lead to differences in consumption growth rates. This is true even if geographic differences alter the returns of household's capital; the levels of household capital adjust to restore equilibrium
$F_K(K_{h,t},G_{h,t}) = F_G(K_{h,t},G_{h,t})$.[46] This assumption is necessary because we do not observe the productivity of capital. The challenge now is how to empirically estimate this model with the data available for Ecuador. Broadly similar models have been estimated for China (Jalan and Ravallion, 2002) and for Peru (de Vreyer et al, 2002), but in both cases panel data were available.

Empirical Model Considerations and Caveats

[46] Within a region the level of capital adjusts (i.e. investment occurs) such that $F_K=F_G$. Nonetheless, $F_{Ki} \neq F_{Kj}$ for any pair i,j.

For many developing countries there is a dearth of panel data where specific individuals are followed over time, and the case of Ecuador is no exception. Cross-sectional surveys are carried out, which leads to multidimensional data in which the samples are different every time period making it nearly impossible to track the same individuals or households over time.

To estimate the augmented consumption model that examines the presence of areas with persistently low levels of income or consumption, this paper proposes the construction of a dynamic pseudo-panel data.[47] A pseudo-panel tracks cohorts of individuals over repeated cross section surveys (Deaton, 1985). As detailed in McKenzie (2004) dynamic panels are recommended if the sample size is “sufficiently large" so that the asymptotic properties of the panel hold.[48] This is discussed in details in the next subsection.

Given that a new sample of individuals is taken in each period, the use of a pseudo-panel reduces the common problems of attrition and non-response faced in typical panel data. Furthermore, pseudo-panels are very often substantially larger, both in number of individuals or households and in the time period that they span. The presentation below closely follows MacKenzie (2004) and Verbeek (2007).

The Empirical Model

A convenient starting point for estimating the model discussed above is the cohort population version of changes in consumption growth rates. Let the population be divided in C cohorts and the data generating process for household i(t) in cohort c is then assumed to be given by

$$\Delta y_{i(t),t} = (\beta - 1) y_{i(t),t-1} + X'_{i(t),t}\gamma + \alpha_{i(t)} + \mu_{i(t),t} \qquad (3.6)$$

$$\alpha_{i(t)} = \alpha_c + \omega_{i(t)}$$

[47] Also called “time-series of repeated cross sections” or “synthetic panels”

[48] McKenzie (2004) and Verbeek and Vella (2005) apply Monte Carlo simulations to check if asymptotic theory provides a realistic approximation of the finite sample properties of pseudo-panel data estimators, an issue that is beyond the scope of this paper.

$$c = 1,\ldots, C \,;\, i(t) = 1,\ldots, N;\, t = 1,\ldots,T$$

where y is the logarithm of household consumption expenditure, X is a vector of exogenous variables including the geographical variables and $\alpha_{i(t)}$ are the non-observed household specific fixed-effects. We assume that the fixed effects are randomly distributed around the cohort population mean effect α_c (cohort fixed effects) and that the parameters are homogeneous within cohorts.[49] Note that the functional dependence of the index i = i(t) is used to highlight the fact that different individuals are observed across time. Finally, β, γ, y, and α_c are the parameters to be estimated.

In the case of a genuine panel data, the parameters in equation (3.6) could be consistently estimated (for fixed T and N →∞) by the Anderson and Hsiao (1981) instrumental variables estimators; or more efficiently by the Generalized Method of Moments (GMM) estimator of Arelano and Bond (1991). These estimators are based on the first difference—as in equation (3.6)— and then using lagged values of the dependent variable as instruments. In pseudo-panel data the variable $y_{i(t),t-1}$ is not observed (as the individuals at t-1 are not the same as the ones at t) limiting the use of these methods. Estimation restrictions are carried out even when we consider cohort averages as in the following equation:

$$\Delta \bar{y}_{c(t),t} = (\beta\text{-}1)\ \bar{y}_{c(t),t-1} + \bar{X}'_{c(t),t}\gamma + \alpha_c + \bar{\omega}_{c(t)} + \bar{\mu}_{c(t),t} \qquad (3.7)$$

where c(t) stands for the mean values of all individuals in cohort c observed at time t; for example $\bar{y}_{c(t),t} = (1/n_c)\sum_{i=1}^{n_c} y_{i(t),t}$. Even though $\bar{y}_{c(t),t-1}$ is not observed, the lagged dependent variable $\bar{y}_{c(t-1),t-1}$ is an unbiased estimate when the cohort sizes are sufficiently large (Verbeek, 2007).

An empirical model that considers cohorts of individuals c = 1,…, C and time t = 1,…,T is:

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[49] As a Moffit (2003), we are also assuming that migration is minimal and does not affect the our model's prediction and that there are no births or deaths— i.e. it is assumed that the number of households are somewhat constant.

$$\Delta \bar{y}_{c(t),t} = \alpha_c + (\beta\text{-}1)\bar{y}_{c(t-1),t-1} + \bar{X}'_{c(t),t}\gamma + \varepsilon_{c(t),t} \quad (3.8)$$

$$\varepsilon_{c(t),t} = (\beta\text{-}1)(\bar{y}_{c(t),t-1} - \bar{y}_{c(t-1),t-1}) + \bar{\omega}_{c(t)} + \bar{\mu}_{c(t),t}$$

It can be shown that in (3.8) the regression error $\varepsilon_{c(t),t}$ is correlated with the lagged dependent variable $\bar{y}_{c(t-1),t-1}$ in finite samples, biasing the results of the OLS estimation of β and γ. Note, however, that this is a direct consequence of measurement error from considering different individuals at time t and t – 1, and not the typical genuine panel data reason that there is a correlation of the lagged dependent variable and the individual effect. Asymptotic theory indicates that the bias is significantly reduced when the cohort sample sizes tend to infinity since both $\bar{y}_{c(t),t-1}$ and $\bar{y}_{c(t-1),t-1}$ are unbiased estimates of the cohort mean.[50] The error term, $\varepsilon_{c(t),t}$ is then randomly distributed and OLS can be used to estimate (3.8).

The asymptotic behavior of pseudo-panel data estimators are derived using alternative asymptotic theory since there are two additional dimensions – the number of cohorts (C) and the number of observations per cohort (n_c) - to the standard panel data dimensions N and T. As shown in MacKenzie (2004), Verbeek and Vella (2005), and Verbeek (2007) one can consider the asymptotic properties of the pseudo-panel and estimate equation (3.8) consistently by OLS which corresponds to the standard within estimator. Verbeek and Vella (2005) refer to a specification like 3.8 as the augmented IV estimator and highlights that it is equivalent to using instrumental variables (IV) with the cohort dummies as instruments in a pseudo-panel or OLS to the model where all variables are replaced by their cohort sample averages; concluding that equation (3.8) can then be consistently estimated by OLS. The asymptotic properties have been used in several important empirical papers. The sample sizes differ considerably, for example Browing, Deaton and Irish (1995) use T=7, C=16 and on average 190 observations per cohort while Propper, Rees and Green (2001) use T=19, C=70 and an average of 80 observations per

[50] As in Antman and McKenzie (2007) our identifying assumption is that a law of large numbers applies within a cohort, so that as the number of individuals within a cohort $n_c \rightarrow \infty$, $(\frac{1}{n_c})\sum_{i=1}^{n_c}\varepsilon_{i,t} \xrightarrow{p} 0$

cohort. Another example is Blundell, Duncan and Meghir (1998) that have T=25, C=8 and an average of 142 observations per cohort. The details of our pseudo-panel are given in the next section; we use T=4, C=36 and an average of 370 observations per cohort in urban areas and 430 observations per cohort for rural areas.

4. Data and Results

The Data

We use the National Ecuadorian Household Survey (ECV, *Encuesta de Condiciones de Vida* - Survey of Living Conditions), which are carried out by the National Institute of Statistic and Census (*Instituto Nacional de Estadística y Censos*, INEC) using similar questionnaires for the last four ECVs.[51] Each survey consists of information on different aspects of household welfare, including household income and consumption, production, health, education, employment, and access to public goods and services.[52] The variable that measures consumption is calculated (and cross-checked) by four different Ecuadorian institutions in the context of a national effort to estimate consumption-based poverty and inequality indicators.[53] The consumption variable takes into account home production, imputed rents, as well as the consumption of durable goods and is expressed in 2006 American dollars.

The information on the geographic characteristics including climate, altitude, precipitation and the availability of infrastructure are official data.[54] In the analysis, we will follow the political division of the country. Ecuador is divided into 22 provinces, which are divided into 205 cantons, which are subdivided into parishes.[55] Finally, the database contains information about the geographical variables according to the canton and parishes of residency. Appendix F

[51] In Ecuador the ECV was carried out in 1995, 1998, 1999, and 2006.
[52] The household survey data is publicly available. However, details pertaining to the measurement issues considered in the official calculations of poverty and inequality indicators as well as the precise geographic locations have not been released to the public domain. Detailed information can be found at www.inec.gov.ec/ECV/bases/ecv.html.
[53] INEC, SENPLADES, CISMIL and MCDS
[54] Produced and maintained by (Ministry of Development Effectiveness) MCDS (2007).
[55] http://www.ecuador.org/esp/clima.htm

contains information on the sources and the variables used. As a group, these variables describe the natural characteristics as well as the geographical capital since they include measures of public and private infrastructure, soil, and altitude. It also contains information on ethnicity and socio-economic status of the individuals.

Construction of pseudo-panels and cohorts

Since the geographic or spatial factors are different for urban and rural areas, we construct two pseudo-panels to take into account such differences. The cohorts are constructed using the last four ECVs surveys as indicated in Deaton and Paxson (1994) and Deaton (1997) and following the recommendations of Verbeek (2007) regarding the size of the cohorts and the variables chosen to construct the cohorts. In this case, our cohorts are formed of individuals selected randomly and grouped according to date of birth and years of education of the household head; both variables are time independent (assuming household heads have completed all their schooling) and allow each individual to be classified in only one cohort. According to Verbeek (2007), choosing these variables are important to maintain the asymptotic properties of the pseudo-panel since this prevents cohorts from being too small. Considering each birth year of the household head to create the cohorts would have led to small sample sizes, especially in rural areas. This is due to the sample design of the household survey since national household surveys generally have smaller samples in rural areas.[56]

The cohorts were constructed considering date of birth of the household head grouped into 5 year intervals from 1930 to 1974 (1930-1934, ..., 1970-1974), including only those between 21-65 years old in 1995 and between 32-76 years old in 2006. Years of education were grouped differently for urban and rural areas. For rural areas we select the following 4 groups: 0-2 years, 3-5 years, 6 years, and 7 years or more. For the urban area the groups are 0-5 years, 6 years, 7-11

[56] Rural areas require smaller samples because they represent a smaller share of the total population, and the variance among the socioeconomic variables is also smaller. Key household characteristics in rural areas tend to be more homogeneous than in urban areas.

years, and 12 or more years. The cohorts have on average 370 and 430 individuals for the urban and rural areas, respectively.[57]

Following the construction of the cohorts, a set of variables are combined into the data set, including consumption, socioeconomic characteristics of households, and geographic variables according to the cantons and parishes of household residency. Using this information, the panels are generated by averaging all variables at the cohort level. It is worth noting that because the geographical capital can affect household welfare through land productivity, health conditions, frequency and intensity of natural disasters, and access to markets (Gallup et al., 2003), the variables selected not only describe the geographical (natural) patterns but also account for differences in infrastructure, availability of public goods and services, and agricultural conditions such as areas with permanent crops.

Descriptive Statistics

Table 3.1 summarizes the descriptive statistics. The average and standard deviation are calculated using the urban and rural pseudo-panels separately.[58] The differences across areas are noticeable; in particular consumption levels in urban areas are generally higher (double than in rural areas) indicating the importance of the relationship between consumption growth and geography that will be considered in the empirical section. Not surprisingly, in urban areas there is more evidence of agglomeration economies as it has a higher number of students per school, less health facilities per capita, and fewer roads per capita; access to credit for agriculture and irrigation are also more abundant in urban areas. Note that the variables related to agricultural activity in urban areas are likely to refer to units that are owned or managed by the residents in these areas.

[57] A reduced number of the 288 cohorts have less than 100 individuals which were maintained to take advantage of having a balanced panel.
[58] Finally, in order to calculate averages and generate descriptive statistics prior to estimation, we considered cohorts' averages as indicated in equation (4.3) taking into account the weights so that the panel would be representative at the national level.

The geographic capital in rural areas is noticeably higher in variables related to agriculture such as large quantity of farmed lands and transitory crops, as well as to the expenditure per acre of fertilizers and pesticides. Another salient feature of the data is that geographical capital in rural areas is generally more dispersed (ratio of the standard deviation to the mean) than in urban areas; this is the case for pure geographical conditions as well as productive infrastructure, basic services and socioeconomic characteristics of the localities of residence, which is likely to affect consumption at the household level. Finally, it is worth noting the difference in human capital of urban and rural households. Urban households are on average more educated and are more likely to have a formal job. Variables such as years of education of the household head, employment status of family members, presence of young children and elderly people are examples of the human capital disparities between urban and rural areas. [59]

Empirical Results

This subsection presents the results of an empirical test that sheds light on the presence of spatial or geographical poverty traps by analyzing the effects of geographical factors on the growth rate of consumption (Jalan and Ravallion, 2002). The proposed test consists of regressing the growth rate of consumption at the household level on geographic variables, allowing for heterogeneity at the micro growth process. Following this alternative, we estimate the consumption model specified in the equation (3.8), taking into account the differences in the growth process at cohort level (fixed effects at this level). As previously discussed, without the fixed-effects, significant coefficients on geographic variables are likely to include the effects of unobserved spatially autocorrelated household characteristics. We follow the pseudo linear dynamic model literature, consider the asymptotic properties of cohorts constructed with large numbers of observations, and use panel OLS estimation to check for the presence of geographic poverty traps (McKenzie, 2004; Verbeek and Vella, 2005; Antman and McKenzie, 2007; Verbeek, 2007). The consumption model is estimated controlling for the household socioeconomic characteristics—control variables. With these controls, the significance of geographical variables will indicate the

[59] The availability of roads and health clinics may seem to be higher in rural areas at first glance. Note that in per capita terms this is not true (the population density of urban areas is about 6 times the one in rural areas).

existence of geographic poverty traps. That is, households with the same socioeconomic characteristics may have different consumption growth rates because they live in places with different geographic capital. The results of the empirical test are summarized in table 3.2 for rural and urban areas.

The results depicted on table 3.2, i.e. the presence of significant geographic variables indicates that geographic capital matters for consumption growth at the individual (or household) level. Households with the same profile have a different expected consumption growth due to the geographical capital of the place where they live. All the signs of the regression coefficients for these variables are as expected, although one of them differs for rural and urban areas, reflecting the complexity of the interactions between geography and consumption growth: while residence in mountain provinces negatively affect consumption in urban areas, it positively affect consumption in rural areas. In particular, for urban areas the residence in mountain provinces means to be away from an exit to sea and export ports, and for rural areas it means proximity to economically important cities as Quito and Cuenca.

Geographical variables explain part of the spatial consumption growth differences. In rural areas, we find that the availability of agricultural inputs such as irrigation services, access to fertilizers and pesticides, and roads (even if non-paved) positively influence household consumption; note that the coefficients on both irrigation and access to fertilizers and pesticides, which proxy for the modernization of the agriculture sector, are much smaller than that of access to roads, indicating the importance of public investment at the local level. Furthermore, the presence of infrastructure in the form of health and education facilities, positively affects consumption growth, indicating that households benefit from the availability of these services. The same is true if considering farmed land per capita, indicating that consumption growth is higher in places where land is used more extensively.

For urban areas, geographical variables such as temperature and variations in altitude have a negative effect on household consumption growth differences. It is interesting to note that these purely geographical variables are not statistically significant for rural areas, with the exception of residence in mountainous provinces, reinforcing the importance of agricultural activities and the existence of basic infrastructure. It is noteworthy how conditions of social exclusion, such as the presence of spatial concentrations of afro descendent population, adversely affect consumption growth. The negative and statistically significant effect of afro-descendent share of the population on household consumption growth indicates that conditions of social exclusion are at play; for instance, segmented labor markets may lead to lower access of afro-decedent households to well-paying jobs.

Results in Table 3.2 corroborate the empirical strategy. The empirical results support the relevance of estimating the consumption growth model accounting for fixed effects at the cohort level. First, high values of the correlation between the cohort effects and other independent variables (the term corr (α_c,Xb) in Table 3.2) indicate that fixed effects at the cohort level should be used. Second, the value of *rho* is another statistic that indicates how much of all residual variance is due to the fixed cohort effects. These values for both areas suggest that almost all the variation is related to cohort differences indicating that an important part of consumption heterogeneity due to unobservable factors corresponds to the variation at the cohort level. In addition to the previously mentioned evidence, we use the Hausman test for fixed effects.[60] Hausman test's null hypothesis –that the random effects estimator is consistent– is rejected for urban and rural areas. Therefore, because the regressors are correlated with α_c, the fixed effect estimator is consistent.

Critical values to avoid poverty traps

After finding that geographic variables influence consumption growth, following Jalan and Ravallion (2002), we estimate the critical values of each geographic variable. The critical value is determined at a point in which consumption growth is zero, keeping the other geographical variables and controls constant. The calculation is simple and the results are intuitive as this

[60] With the Stata option "sigmamore", this specifies that both covariance matrices are based on the (same) estimated disturbance variance from the efficient estimator. Sigmamore is recommended when comparing fixed-effects and random-effects in linear regression because they are much less likely to produce a non-positive definite differenced covariance matrix.

indicates if the critical values for a geography poverty trap occur within the boundaries of the data. As previously discussed, one might find that higher endowments of geographic capital increase the marginal product of household capital, it may still be the case that no area in our sample has so little geographic capital to entail falling consumption. The critical values are calculated using the coefficients of the consumption growth model that takes into account the control variables and the fixed effects at the cohort level. All the other variables are kept at their sample mean values.

From equation (3.8), the critical values, $\overline{X}_j^*$ are calculated as:

$$\overline{X}_j^* = \overline{X}_j - [\hat{\alpha}_c + (\hat{\beta} - 1)\overline{y}_{c(t-1),t-1} + \overline{X}'_{c(t),t}\,\hat{\gamma}] / \hat{\gamma}_j$$

where j is the geographic variable under consideration and the parameters take its estimated values.

The analysis considers only the variables that according to our previous analysis, significantly affect consumption growth; Table 3.3 reports the critical values for such variables. We consider only the variables related to infrastructure and the provision of services and estimate the boundaries for urban and rural areas separately. Furthermore, the estimation was carried out using the mean values of the independent variables for two periods: 1995-1999 and 1999-2006, periods of economic recession and growth, respectively. During the recessionary period (1995-1999) real consumption (in constant values) decreased on average 9 percent annually in urban areas and on average 10 percent annually in rural areas, and on the growth periods consumption increased on average 5 percent annually for both areas.

We find that, in general, geographic capital can constrain consumption growth; this is especially true for recessionary periods. The critical values are higher during the in the 1995-1999 period than in the 1999-2006 period, the exception is the percentage of the surface with transitory crops, which by contrast is higher in expansionary periods. The results in Table 3.3 also indicate that for rural areas, inputs to agricultural activities such as the use of fertilizer and pesticides and irrigation are less limiting than in urban areas. There is also evidence that, during periods of recession, in order to obtain positive consumption growth in the rural areas the size of the farmed land is an important limitation: it needs to be on average almost 8 times larger. In more favorable economic times, there are other limiting factors which are more related to household socioeconomic characteristics (or other variables not considered in the analysis and not necessarily related with geographic variables). In the case of urban areas, geographic variables are not a limiting factor, as the critical values are below the average values, although they might be obstacles to higher growth, as Table 3.3 shows.

5. Final Remarks

The geography-poverty nexus has been hotly debated by academic and policy makers. In this paper we construct and use a pseudo dynamic panel data of household and geographic variables to gauge the effects of geographic variables on household consumption growth. The results indicate that geographic factors play a significant role in explaining differences in household consumption growth in Ecuador. The estimations are consistent with the hypothesis that geographical capital affects consumption, even after accounting for household characteristics.

The literature on poverty traps suggests that geographic factors such as altitude and temperature as well as infrastructure and the provision of public capital are important in explaining why some localities remain persistently poor. The significance and impact of geographical variables differ across urban and rural areas, indicating the heterogeneous determinants of household consumption growth. In addition, given Ecuador’s geographical diversity, the results are consistent with the fact that household socioeconomic factors alone cannot fully explain differences in consumption growth.

Since the evidence shows that geographic factors have played a significant role in explaining the dynamics of household consumption, poverty reduction programs should take into account such factors. Social programs aimed at reducing the incidence of poverty in specific localities could be enhanced by concomitantly improving the provision of local infrastructure and market access (logistics, relocation costs) in addition to directly targeting household welfare.

The existence of poverty traps inhibits economic development even in the presence of economic growth. The empirical detection of poverty traps remains a challenge among researchers due to the lack of long panels of data and the presence of measurement error and attrition. This paper tests the effect of local geographic endowment of capital on household growth on living standards using a pseudo panel data for Ecuador. This paper tests the existence of geographical poverty traps by identifying the impact of local geographic and socioeconomic variables on consumption growth while removing unobserved household and community level fixed effects. The results indicate that private consumption growth depends on local geographic variables suggesting the presence of spatial poverty traps.

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Table 3.1 : Descriptive Statistics

Variables*	Urban		Rural	
	Average	St. dev	Average	St. dev
Consumption- per capita (2006$ per month)	122.51	67.50	71.31	53.49
Geographical (canton or parish level)				
Residence in Mountain Provinces	0.551	0.122	0.462	0.134
Average rainfall (mm per year)	1065	111	1309	210
Average temperature (°C)	20.06	1.20	18.42	1.86
Range of altitude (meters over sea level)	1045	158	1077	227
Index of natural disasters (0-12)	7.968	0.301	6.878	0.606
Direct distance (minutes)	97.38	10.42	92.43	11.63
Student per classroom in secondary	258.3	18.6	117.3	27.7
Fertilizers and pesticides Expenditure per acre	32.1	158.8	90.9	110.6
Agricultural units with access to credit (%)	9.572	1.455	7.817	1.688
Surface with permanent crops (%)	10.84	2.85	10.16	3.31
Surface with transitory crops (%)	10.79	2.25	15.56	3.33
Roads 1st order (km per capita)	0.299	0.068	0.576	0.129
Roads 2nd order (km per capita)	0.153	0.064	0.631	0.315
Farmed land per capita (acres)	1.109	9.719	2.346	5.775
Health facilities without admission (per 10	1.670	0.127	3.707	0.964
Surface with access to irrigation (%)	52.00	9.01	17.34	5.21
Infant mortality rate (per thousand)	18.98	1.08	15.32	5.46
Afro descendent population (%)	0.059	0.012	0.048	0.030
Controls (household level)				
Age of household head	47.48	13.41	47.47	13.49
Years of education of household head	8.050	4.457	5.442	3.842
Proportion of children aged 6-11	0.125	0.062	0.152	0.070
Proportion of children aged 12-14	0.063	0.035	0.074	0.041
Proportion of children aged 15-17	0.063	0.034	0.065	0.036
Proportion of members aged 18 to 59	0.528	0.105	0.458	0.102
Proportion of employed	0.215	0.057	0.097	0.070
Proportion of self-employed	0.102	0.055	0.115	0.062

* all monetary figures are in US dollars.
Source: INEC “Agro National Census 2000”, “Population and House Census 2000” and “ECV” four surveys between 1995 and 2006; Secretaría Técnica del MCDS “SIISE 4.5”; and Official data from the Ministries and other public institutions.

Table 3.2: OLS Consumption Model with cohort fixed effects (*) - Pseudo panel 1995-2006

(Dependent Variable: Differential of logarithm of household consumption per capita) (**)

Variables	OLS estimation					
	Urban Areas			Rural Areas		
	Coef.	SE		Coef.	SE	
Lagged per capita consumption	-0.943	0.081	***	-1.266	0.040	***
Geographical (canton or parish level)						
Residence in Mountain Provinces	-0.437	0.118	***	0.614	0.091	***
Average rainfall (mm per year)	0.001	0.000	*	0.000	0.000	
Average temperature (°C)	-0.110	0.064	*	-0.001	0.011	
Range of altitude (meters above sea level)	-0.001	0.000	***	0.000	0.000	
Index of natural disasters (0-12)	-0.010	0.112		-0.054	0.040	
Direct distance (minutes)	0.003	0.004		-0.004	0.002	**
Student per school in secondary	0.004	0.002		0.002	0.001	**
Fertilizers and pesticides expenditure per acre	0.000	0.000	**	0.001	0.000	***
Agricultural units with access to credit (%)				0.011	0.013	
Surface with permanent crops (%)	-0.011	0.012		-0.018	0.005	***
Surface with transitory crops (%)	-0.016	0.013		-0.023	0.007	***
Roads paved (km per capita)	2.417	0.419	***	0.004	0.093	
Roads unpaved (km per capita)	1.424	0.335	***	0.101	0.053	*
Farmed land per capita (acres)	-0.008	0.032		0.007	0.001	***
Health facilities without admission (per 10 thous)	-0.053	0.241		0.040	0.018	**
Surface with access to irrigation (%)	0.013	0.006	**	0.008	0.003	**
Infant mortality rate (per thousand)	-0.004	0.016		0.001	0.002	
Afro descendent population (%)	-5.636	1.800	***	-1.450	0.437	***
Controls (household level)						
Age of household head				-0.003	0.007	
Years of education of household head	0.012	0.055		0.154	0.028	***
Proportion of children aged 6-11	0.433	0.532		0.319	0.477	
Proportion of children aged 12-14	0.449	0.739		-1.491	0.637	**
Proportion of children aged 15-17	0.842	0.856		0.381	0.699	
Proportion of members aged 18 to 59	-0.473	0.211	**	0.009	0.146	
Proportion of employed	0.566	0.489		0.218	0.335	
Proportion of self-employed				0.161	0.201	
Household size (logarithm)	-0.938	0.144	***	-0.350	0.124	***
Proportion of adults with primary educ.	-1.047	0.542	*	-0.762	0.309	**
Constant	5.908	1.873	***	4.716	0.740	***
R-squared						
Within	0.9430			0.9820		
Between	0.2432			0.0839		
Overall	0.4170			0.5739		
corr(α_c, Xb)	-0.6816			-0.6535		
Rho (fraction of variance due to α_c)	0.8857			0.9443		
Hausman test (Ho: Cohort effects are random)						
Chi2	51.35			53.66		
Prob>Chi2	0.0006			0.0007		

Notes: (*) With robust estimator of variance of parameters. (**) Not all geographical information available was incorporated in the urban-rural regressions. Due to multicollinearity, some variables were excluded. Alternative specifications are also available upon request.

*, **, *** indicate that the variables are significant at 10%, 5% and 1%, respectively.

Table 3.3: Critical Values to Avoid Geographic Poverty Traps

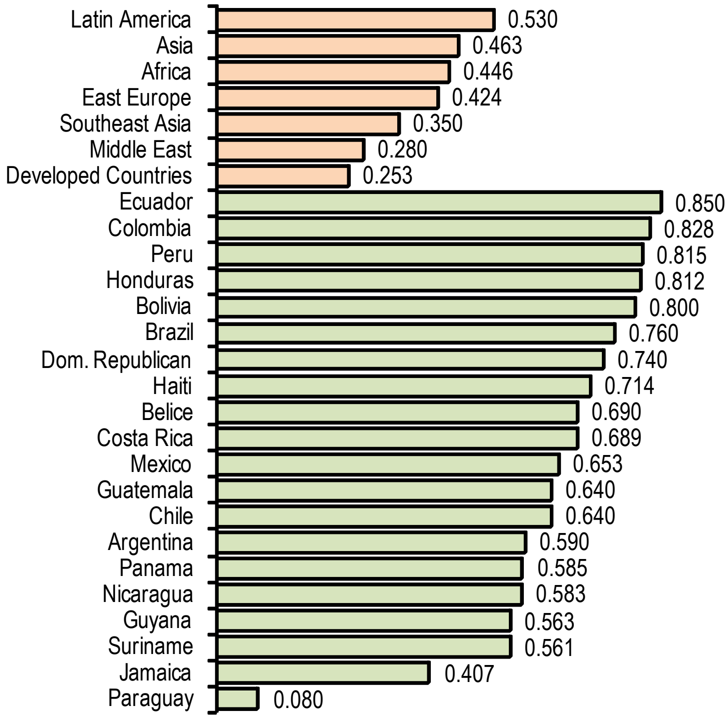
	Level	Urban				Rural			
		Critical	Average	Min	Max	Critical	Average	Min	Max
1995 – 1999 (recession)									
Student per school in secondary	Parish					194	123	57	222
Fertilizers & pesticides expenditure per acre	Canton	471	31	0	1788	273	84	0	931
Surface with permanent crops (%)	Canton					3.3	10.0	3	27
Surface with transitory crops (%)	Canton					10	15	7	23
Roads 1st order (km per capita)	Canton	0.37	0.30	0.12	0.46				
Roads 2nd order (km per capita)	Canton	0.28	0.16	0.04	0.41	1.8	0.60	0.05	1.56
Farmed land per capita (acres)	Canton					19	2.4	0.0	47
Health facilities without admission (per 10 thous)	Parish					6.7	3.6	1.2	6.7
Surface with access to irrigation (%)	Canton	65	52	22	80	31	16	8	35
1999 – 2006 (expansion)									
Student per school in secondary	Parish					66	115	84	222
Fertilizers & pesticides expenditure per acre	Canton	0	28	0	503	0	82	0	504
Surface with permanent crops (%)	Canton					16	12	3	27
Surface with transitory crops (%)	Canton					20	17	6	22
Roads 1st order (km per capita)	Canton	0.25	0.28	0.16	0.46				
Roads 2nd order (km per capita)	Canton	0.08	0.14	0.04	0.31	0.0	0.5	0.05	1.33
Farmed land per capita (acres)	Canton					0.0	2.3	0.0	47
Health facilities without admission (per 10 thous)	Parish					1.5	3.6	1.2	5.7
Surface with access to irrigation (%)	Canton	46	52	34	77	10	21	8	35

Note:
Average annual consumption growth 1995-1999: Urban -9%, Rural -10%
Average annual consumption growth 1999-2006: Urban 5%, Rural 5%
Average annual consumption growth 1995-2006: Urban -0.2%, Rural -0.5%
Source: Author's calculation's. Includes only significant variables related to public infrastructure and services

Figure 3.1

Source: Gallup, Sachs and Mellinger, 1999

Figure 3.2: Index of Geographical Fragmentation



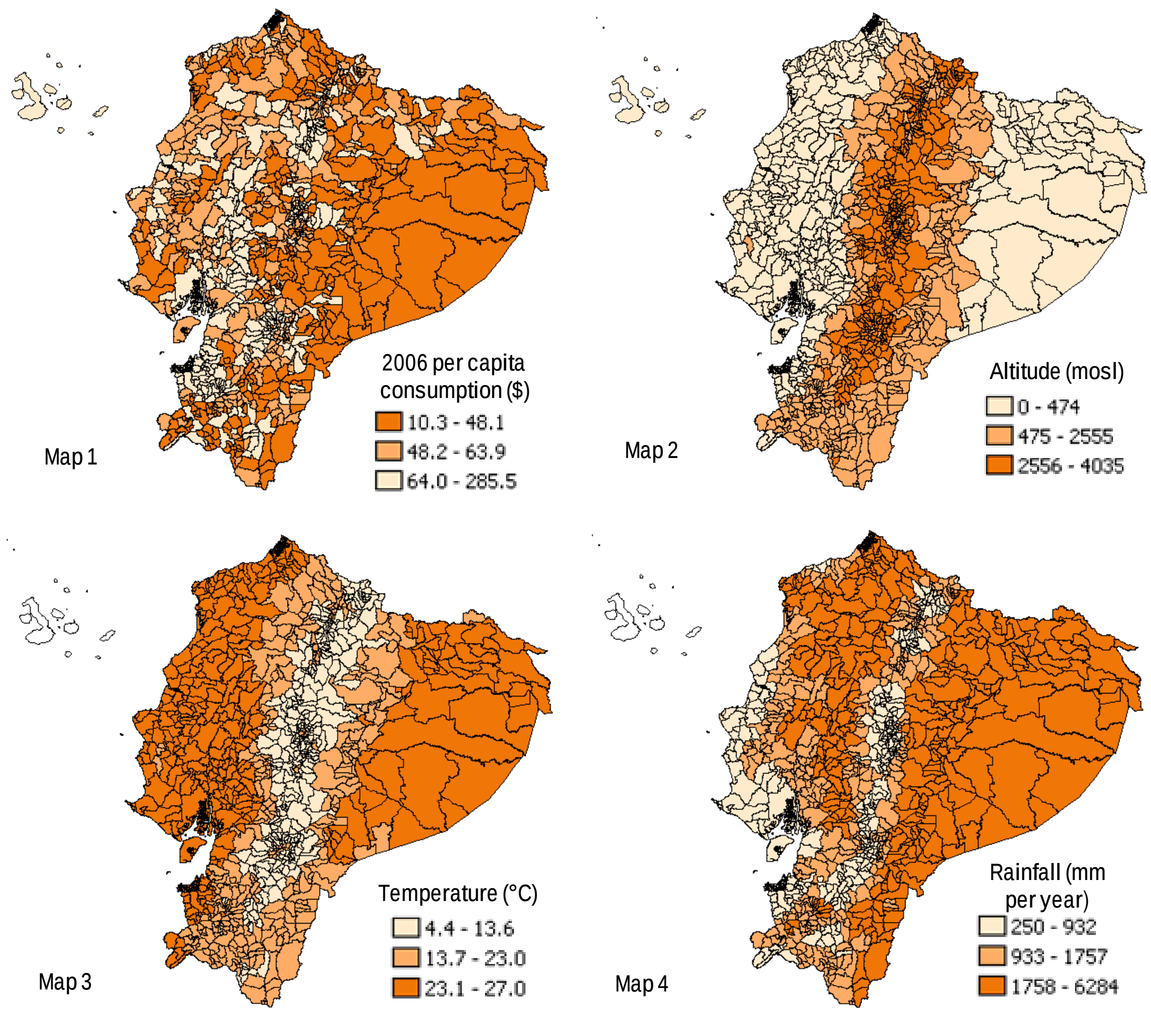
Source: Gallup, Gaviria, and Lora (2003)

Note: The index of Geographical Fragmentation is defined as the probability that two individuals taken at random from the population live in similar ecozones. The index goes from zero, where all the population is settled in the same ecozone to the hypothetical case where each individual comes from a different ecozone.

Figure 3.3: Consumption and geography in Ecuador (Correlations (at the parish level)

	Consumption per capita ($)	
	w/t Weights	Weighted*
Altitude (masl)	0.0475	0.2880*
Rainfall (mm x year)	-0.2371*	-0.2110*
Temperature (°C)	-0.0741*	-0.2817*
Pop density (Indiv x km2)	0.5117*	0.8238*

* Considering population size at the parish level. ** Significant at 1% or 5% significance levels.



Appendix A: Current and alternative income targeting models

Model of log per capita household income (1)

Variables	Coef
Demographics	
Household size (log)	-0.697***
	(0.010)
Demographic Dependency	-0.074***
	(0.006)
House / Household	
Dwelling and household deprivations Index	-0.096***
	(0.002)
Number of rooms	0.082***
	(0.003)
Household head	
Schooling (1 more than 9 years, 0 otherwise)	0.250***
	(0.009)
Wage earner (1 non-earner, 0 otherwise) (3)	0.344***
	(0.020)
Other members	
Employment of older than17 years (4)	0.110***
	(0.005)
Wage earner without benefits	-0.240***
	(0.009)
Geographic	
Area of residence (1 rural, 0 urban)	-0.040***
	(0.010)
Patrimony poverty at municipality level (5)	-0.006***
	(0.000)
Constant	9.384***
	(0.023)
Adjusted R Square	0.676
Number of observations	20350

(1) Estimated with robust standard errors
(2) Sum of 20 dummy variables expressed as deprivations
(3) in a household's business
(4) 1 employed (no spouse or household head), 0 otherwise
(5) from www.coneval.gob.mx
Note: standard errors between brackets
Source: Author's calculation based on INEGI "ENIGH 2006"

Current and updated discriminant model (SUP)*

	Current*	Updated**
Overcrowding: number of persons per room	0.139	0.214
Demographic Dependency:	0.176	0.203
Female head of household	-0.02	-0.131
Households with children aged 0-11	0.255	0.277
Age of the household head	0.005	0.004
Does not have access/right to medical service	0.475	0.47
Head of household with 0 years of education	0.38	0.3
Head of household with 1-5 years of education	0.201	0.207
Dwelling with shared or no bathroom	0.415	0.316
Dwelling with bathroom no water connection	0.22	0.273
Dwelling with dirt floor	0.475	0.571
Household without gas or electrical stove	0.761	0.727
Household without refrigerator	0.507	0.356
Household without washing machine	0.127	0.28
Household without car or truck	0.159	0.268
Dwelling rural area	0.653	-0.053
Dwelling in region1, 2 y 3	-0.516	-0.618
Dwelling in region4	-0.51	-0.64
Dwelling in region5	-0.328	-0.56
Dwelling in region6	-0.352	-0.458
Dwelling in region7	-0.657	-0.699
Dwelling in region8 y 9	-0.391	-0.516
Dwelling in region10 y 17	-0.293	-0.744
Dwelling in region11	-0.511	-0.631
Dwelling in region12	-0.66	-0.701
Dwelling in region13	-0.376	-0.663
Dwelling in region14	-0.413	-0.767
Dwelling in region15	-0.143	-0.671
Dwelling in region16 y 19	-0.07	-0.436
Constant	-0.579	-1.315
Number of observations		20327
% true classification		83.1

* estimated with 2000 ENIGH data
** estimated with 2006 ENIGH data (capabilities poverty as dep variable)
Note: coefficients are from Canonical discriminant function
Source: Author's calculation Based on INEGI "ENIGH 2000 and 2006"

Appendix B: Microsimulation model and the impact of transfers on education

It models the discrete variable, S_{ij}, which expresses the labor force participation and attendance of a child living in the household i. This indicator variable takes the value of zero (S_{i0}) when the child goes to school; it is equal to one (S_{i1}) when the child is studying and working outside the home; and the value of two (S_{i2}) when the child is studying and not working outside the home. We assume that household i choose option j based on a utility function ($U_i(j)$) that depends on the characteristics of the child, home and educational supply (Z_i), the child's contribution to household income (y_{ij}), household income less the child's income (Y_{-i}) and a random variable that expresses the unobserved heterogeneity of family behavior (v_{ij}). Thus, the household i chooses option k if and only if $U_i(k) + v_{ik} > U_i(j) + vij$ for $k \neq j$.

We assume that the functional form of $U_i(j)$ is linear:

$$U_i(j) = Z_i\gamma_j + (Y_{-i} + y_{ij})\alpha_j + v_{ij},$$

where γ and α are the parameters to be estimated. We also assume that the child's income for his work in the labor market (w_i) are determined according to a standard model of labor income:

$$\log w_i = X_i\delta + m^*E + u_i,$$

where X_i are the child's individual characteristics; E is a dummy variable that takes value of 1 if the child studies and works is zero otherwise; u_i is the random term representing unobserved heterogeneity in earnings; and δ and m are the parameters to be estimated.

The child's working income (in the market and at home, y_{ij}) is proportional to their actual or potential income earned in the market (w_i):

$$y_{i0} = Kw_i,\ y_{i1} = My_{i0} = MKw_i,\ y_{i2} = Dy_{i0} = DKw_i,$$

where K is the value of the observed relationship between y_{i0} and w_i, D is not observed and M = exp (m) is obtained from estimating the earnings model. With the above assumptions and specifications, it follows that the utility of household i choosing option j is described as:

$$U_i(j) = Z_i\gamma_j + Y_{-i}\,\alpha_j + w_i\,\beta_j + v_{ij},\ \text{where } \beta_0=\alpha_0K,\ \beta_1=\alpha_1MK \text{ y } \beta_2=\alpha_2DK.$$

Consequently, if α, β, γ, w_i and v_{ij} are known, the choice made by households will be one that maximizes utility. This expression represents the utility of household i for the option j without program transfer, i.e., the reference case. To simulate the impact of transfers we consider poorer households selected with each targeting model, the level of transfers corresponding to the second half of 2006 (which distinguishes age, sex and school grade the child is attending) and assume that corresponsibilities (or conditionalities) are accomplished. The household i will choose the option that maximizes utility $U_i(j)$ among the following options:

(i) If the household is not selected by the targeting model:

$$U_i(j) = Z_i\gamma_j + \alpha_jY_{-i} + \beta_jy_i + w_{ij},\ \text{for } j=0,1,2$$

(ii) If the household is selected by the model:

$U_i(j) = Z_i\gamma_j + \alpha_j(Y_{-i} + A) + \beta_j w_i + v_{ij}$, for j=0
$U_i(j) = Z_i\gamma_j + \alpha_j(Y_{-i} + A + B) + \beta_j w_i + v_{ij}$, for j=1,2

where A is the share of uncomditional transfers and B is the proportion of transfers that are conditional on school attendance. That is, with these transfers, household i will choose k if and only if
$U_i(k) + v_{ik} > U_i(j) + v_{ij}$ for $k \neq j$.

The earnings model is estimated using Ordinary Least Squares (OLS) and the occupational choice model with a multinomial logit. The former provides to the latter the potential earnings of each child, including those who do not work outside the home. With the second model it not possible to know directly the values of γ_j, α_j and β_j because one of the options is taken as reference, that is, the multinomial logit model only estimates $(\alpha_j-\alpha_0)$, $(\beta_j-\beta_0)$ and $(\gamma_j-\gamma_0)$ if the selected reference is j=0. However, with these estimates and indicated assumptions, it follows that:

$\alpha_1 = (a_1-b_1 / K) / (1-M)$,
$\alpha_0 = (\alpha_1-a_1)$,
$\alpha_2 = (\alpha_1+a_2-a_1)$, y
$D = (b_2+\alpha_0K) / (\alpha_2K)$

where a_j and b_j are the estimated coefficients of multinomial logit model corresponding to Y_{-i} and w_i for j=1,2, respectively. Because the residuals cannot be observed in a multinomial logit model, the $v_{ij}-v_{i0}$ was generated for an interval consistent with the observed choice. For example, if household i chooses option 1, $v_{i1}-v_{i0}$ is obtained, after the estimate of both models, such that it satisfies the inequality:

$Z_i\gamma_1 + a_1Y_{-i} + y_i b_1 + (v_{i1}-v_{i0}) > \mathrm{Sup}[0, Z_i\gamma_2 + a_2Y_{-i} + y_i b_2 + (v_{i2}-v_{i0})]$,

which can be achieved if one takes into account the following rules:

$v_{ik} = -\ln[-p_{ik}*\ln()]$ if $j=k$
$v_{ij} = -\ln[\exp(-v_{ik})*(p_{ij}/p_{ik})-\ln()]$ if $j\neq k$

where () = uniform(), a function that produces uniformly distributed random numbers for the interval [0,1).

Further details are provided in the next chapter of this dissertation.

Appendix C: Log Earnings Regression

Log Earnings Regression 12-18 year-old children reporting earnings

	Urban			**Rural**		
	Coef.	t	P>t	Coef.	t	P>t
Works and studies	-0.2522	-2.53	0.0110	-0.5823	-5.78	0.0000
Age	0.1801	5.44	0.0000	0.1244	4.43	0.0000
Years of education	0.0025	0.15	0.8850	0.0278	1.98	0.0480
Dummy for Male	0.0528	0.76	0.4500	0.2045	3.17	0.0020
Log of median wage (12-18 years old)	0.7728	8.88	0.0000	0.8852	15.66	0.0000
School-age gap	0.0157	1.42	0.1560	0.0117	0.98	0.3260
Constant	-1.9179	-2.82	0.0050	-1.8682	-3.88	0.0000
No Observations	764			1046		
R- squared	0.273			0.2842		

Source: Author's calculation based on the 1996 ENIGH

Appendix D: Multinomial Logit - Alternative specification

	Model with parents' education linearly				Model with parents' education dummies (*)			
	Working and studying		Studying		Working and studying		Studying	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Total household income	0.0001	0.0000 *	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Children's earnings (predicted)	-0.0171	0.0009 ***	0.0007	0.0003 **	-0.0171	0.0009 ***	0.0007	0.0003 **
Number of members	-0.0113	0.0293	-0.0001	0.0191	-0.0069	0.0295	0.0061	0.0192
Age	-0.3110	0.0570 ***	-1.0025	0.0374 ***	-0.3141	0.0568 ***	-1.0116	0.0376 ***
Years of education	0.6119	0.0412 ***	0.5127	0.0252 ***	0.6133	0.0411 ***	0.5237	0.0253 ***
School-age gap	0.0571	0.0193 ***	-0.0369	0.0111 ***	0.0596	0.0192 ***	-0.0345	0.0112 ***
Dummy for Male	1.2292	0.0955 ***	0.1307	0.0574 **	1.2355	0.0955 ***	0.1364	0.0574 **
Years of education_head	0.0209	0.0157	0.0721	0.0102 ***				
Years of education_spouse head	-0.0017	0.0186	0.0383	0.0120 ***				
0-5 years of education_head (dummy)					-0.6542	0.2306 ***	-1.1470	0.1487 ***
6 years of education_head (dummy)					-0.6365	0.2311 ***	-0.8783	0.1453 ***
7-9 years of education_head (dummy)					-0.5683	0.2550 **	-0.6184	0.1528 ***
0-5 years of education spouse head (dummy)					0.0309	0.3755	-0.6522	0.2462 ***
6 years of education spouse head (dummy)					0.0688	0.3712	-0.6248	0.2427 ***
7-9 years of education spouse head (dummy)					0.0579	0.3912	-0.4028	0.2479
Age household head	0.0007	0.0048	0.0152	0.0032 ***	0.0009	0.0047	0.0123	0.0031 ***
Age spouse head	-0.0039	0.0031	-0.0015	0.0020	-0.0042	0.0029	0.0007	0.0019
Number of members age 0-5	-0.0284	0.0715	-0.1383	0.0474 ***	-0.0360	0.0719	-0.1529	0.0474 ***
Rural*	-0.8812	0.1074 ***	-0.6562	0.0667 ***	-0.8693	0.1094 ***	-0.6458	0.0668 ***
Northeast*	-1.5359	0.3312 ***	-0.5944	0.1475 ***	-0.2646	0.2236	-0.0571	0.1211
West (Central)*	-1.2775	0.3252 ***	-0.5187	0.1564 ***	1.2672	0.3245 ***	0.5167	0.1576 ***
Central*	-1.7272	0.3538 ***	-0.0511	0.1535	-0.4487	0.1556 ***	0.4626	0.0847 ***
South* -	-1.4964	0.3226 ***	0.3460	0.1438 **	-0.2167	0.1451	0.8435	0.0984 ***
Rank of child (oldest -youngest)	-0.0337	0.0571	-0.0742	0.0364 **	-0.0376	0.0570	-0.0743	0.0365 **
Average distance- primary school**	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Average distance- secondary school**	0.0001	0.0000 **	0.0000	0.0000	0.0001	0.0000 **	0.0000	0.0000
Average distance high-school**	0.0000	0.0000 ***	0.0000	0.0000 *	0.0000	0.0000 ***	0.0000	0.0000 *
Regis. students x teacher (Primary)	0.0743	0.0214 ***	0.0084	0.0149	0.0752	0.0214 ***	0.0087	0.0148
Regis. students x teacher (Secondary)	0.0683	0.0275 **	-0.0312	0.0154 **	0.0657	0.0274 **	-0.0355	0.0155 **
Regis. students x teacher (High-school)	-0.1315	0.0263 ***	-0.0114	0.0159	-0.1314	0.0262 ***	-0.0081	0.0159
Constant	2.4971	0.9914 **	11.8130	0.6225 ***	1.9059	1.0041 *	13.3973	0.6292 ***
Number of obs	10696				10696			
Wald chi2(48)	3400				3378			
Prob > chi2	0.000				0.000			
Pseudo R2	0.371				0.373			

(*) dummy variables for levels of schooling of the parents

*, ** and *** indicate that the variables are significant at 10%, 5% and 1%, respectively.

Appendix E: Tests for the independence of irrelevant alternatives

**** Small-Hsiao tests of IIA assumption (N=10696)

Ho: Odds (Outcome-J vs Outcome-K) are independent of other alternatives.

Omitted	lnL(full)	lnL(omit)	chi2	df	P>chi2	evidence
Working and studying	-1909.33	-1900.75	17.171	25	0.876	for Ho
Studying	-615.28	-599.99	30.581	25	0.203	for Ho

**** Hausman tests of IIA assumption (N=10696)

Ho: Odds (Outcome-J vs Outcome-K) are independent of other alternatives.

Omitted	chi2	Df	P>chi2	evidence
Working and studying	-121.4	20	---	---
Studying	-446.7	21	---	---

Note: If chi2<0, the estimated model does not meet asymptotic assumptions of the test.

Appendix F: Data sources and definitions

This table contains the other sources of the data. After we worked out the panel this information was cross checked with the Ecuadorian authorities, before the estimations were carried out.

From Administrative registries in ministries and other governmental institutions:

At the cantons level:

- Index of natural disasters values between 0-12 (includes risk and current activities of seismic activities; volcanoes; tsunami; land slide , floods and droughts);
- Direct or potential distance between a populated area, main street, street or river to a not so populated area. (expressed in minutes);
- Houses with sewage system connected to public network (percentage of total homes with access);
- Roads 1st order (with asphalt) and roads 2nd order (without asphalt) in kilometers per habitants
- Number of doctors and number of health related staff non doctors (per 10 thousand habitants).

At the parishes level:

- Population density (habitants per kilometer squared)
- Average temperature (in centigrade)
- Average precipitation (millimeters cubical per year);
- Median Altitude (meters above the sea level) and altitude range (difference between the maximum and the minimum altitude)
- Health clinics without rooms or over-night stay (number of clinics per 10 thousand habitants);
- Number of students per teacher in public and private schools for primary and secondary grades

From the Censo Nacional Agropecuario, 2000 (Census on Agriculture and Livestock – year 2000)

At the cantons level:

- Area used for Agriculture and Livestock (UPAs) per person (hectares)
- Area of farming of the UPAs with access to irrigation (% of the total area available for farming)
- Uses of the soil (land): (1) area of the UPAs with permanent cultures (% of the total area); (2) area of the UPAs used on transitory cultures (% of the total area)
- UPAs with access to electricity (% of total UPAs);
- UPAs with access to credit (% of total de UPAs).

Note: UPAs in spanish stands for "Unidades de Producción Agropecuaria"

From the Censo de Población y Vivienda, 2000 (Census on population and Houses- year 2000)

At the parishes level:

- Functional illiteracy (% pop older 15) (percentage of the population older than 15 years old with 3 or less years of schooling)
- Indigenous population (proportion with respect to total population);
- Afro descendent population (proportion with respect to total population);
- Infant mortality per one thousand (Number of kids that die before reaching 1 year old and that were born alive)